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François Cohen

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École doctorale n° 396 : Economie, Organisation, Société

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T H È S E

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présentée et soutenue publiquement par

François COHEN

le 26 septembre 2014

Investir dans l'utilisation et la production d'énergie pour lutter et s'adapter au changement climatique

Investing in energy use and production to mitigate and to adapt to climate change

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This dissertation is dedicated to my parents and to my wife

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Preface

This PhD dissertation has been prepared in the framework of a *Convention Industrielle de Formation par la Recherche*[1] (CIFRE). The Convention was initiated by BIO Intelligence Service, a French private consultancy in environment, member of the Deloitte group. The consultancy hired me to undertake research in the *ex ante* assessment of environmental and energy policies. In the framework of the CIFRE, the consultancy and I have benefitted from the financial support of the *Association Nationale pour la Recherche Technologique* (ANRT) and we have asked Matthieu Glachant, from the Centre d'Economie Industrielle of Mines ParisTech, to supervise my work.

For BIO Intelligence Service, this research allowed improving its processes when assessing the *ex ante* impacts of energy and environmental policies for public authorities. As a research assistant for the company, I was offered the opportunity to acquire a good understanding of EU official processes and in-depth knowledge of the key environmental and energy issues of current political agenda. More concretely, I have worked on 16 socioeconomic studies and on most of the steps of any energy and environmental policy evaluation, from the consultation of stakeholders to the formulation of recommendations to monitor future policy enforcement.

The knowledge and skills capitalized at BIO Intelligence Service have been more than useful to formulate the research question covered with this PhD dissertation. Under the supervision of Matthieu Glachant and benefiting from Magnus Söderberg's support, this PhD dissertation resorts to econometric methods to analyse market data and survey data with the objective of shedding light on consumer attitude towards energy efficiency. Furthermore, two of the chapters of this PhD dissertation were drafted as consultancy services delivered by BIO Intelligence Service to the French Agency of Environment and Energy Management (ADEME) and the Directorate-General for Climate Action of the European Commission (DG CLIMA).

[1] English translation: Industrial Convention of Formation through Research

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Introduction

The fifth report of the Intergovernmental Panel on Climate Change (IPCC, 2013) estimates that global mean surface temperature could be up to 4.8°C higher in 2081-2100 relative to 1896-2005 if greenhouse gas emissions (GHG) continue unabated. Climate change could not only have impacts on eco-systems, but also on all the matters of human activities, including food availability, human settlements, public health and water availability and quality along with industrial and economic activities.

This PhD dissertation aims to understand how energy-related investment decisions will contribute to climate change mitigation and adaptation, defined as all the adjustments “in natural or human systems in response to actual or expected climate stimuli or their effects, which moderates harm or exploits beneficial opportunities” (IPCC, 2001). It focuses principally on the residential sector, which represented the non-negligible share of 24.7% of final EU energy consumption (29% of electricity consumption) in 2011 (Eurostat, 2013) and in which the main decision makers are households whose investment behaviour arguably differs from that of corporations, a pattern that should influence policy design.

This PhD dissertation is divided into two parts and four papers. Although, the papers deal with related issues, each can be read on its own. Importantly, their nature is different. Two of them are research papers which seek to contribute to the economic literature on investment behaviour in energy activities. The other two are policy-oriented. They review the academic and policy literature in order to derive policy lessons for regulators.

The first part looks at energy efficiency investments as a way to mitigate climate change, taking domestic appliances as a case study. It is composed of two chapters. Chapter 1 is about consumer behaviour and the impact of energy prices on the energy efficiency of sold appliances whereas Chapter 2 is a policy paper dealing with the impacts and the implementation of the EU Energy Label. The second part of this PhD dissertation also includes two chapters and focuses on the impacts of climate change on energy investment behaviour. Chapter 3 is a policy-oriented review of the literature on climate vulnerability and adaptation to climate change of electricity supply. Chapter 4 looks at how homeowners adapt their dwellings to climate change using microdata from 1985-2011. We briefly present below each part of this PhD dissertation and our contribution to the existing literature.

Investing in Energy Efficiency for Climate Change Mitigation: the Case of Domestic Appliances

Energy production and consumption are responsible for the great majority of worldwide GHG emissions. They are consequently the principal focus of mitigation policies. Energy efficiency is of particular importance as decarbonising energy production has certain limits. Existing energy infrastructures relying on fossil fuels cannot easily be swapped with renewable sources of energy due to high replacement costs. Moreover, the intermittency of renewable sources of energy (i.e. wind and solar) makes it difficult to raise their share in the energy mix without damaging energy security.

The focus of our study on domestic appliances may be justified on several grounds. First, domestic appliances are responsible for a large share of the energy consumed by households: 16% of the energy consumed in the residential sector and more than 60% of residential electricity consumption in 2009 (Enerdata, 2010).[2] Moreover, the potential for energy efficiency improvements is high: for example, an energy efficient refrigerator can be five times less consuming as an energy inefficient one.[3] There are various market failures that may hinder the diffusion of energy efficient domestic appliances. Finally, these products have benefitted from a large scale information-based policy since 1995: the EU Energy Label.

Numerous policies are being implemented in order to promote energy conservation. In the EU, the MURE database[4] registers around 550 energy efficiency policies that have been or are currently implemented in the European Union, targeting households, transports, industry or the service sector. These policies all contribute to the objective set by the EU to reduce primary energy demand by 20% in 2020 as compared with a "no policy" scenario. In the US, the energy efficiency programs implemented at State level or municipal level is backed up by federal regulations and commitments. For instance, the National Energy Conservation Policy Act was implemented in 1978 and has frequently been updated.

[2] Most of the energy consumed in the residential sector is used for space heating (67% in 2009). Apart from domestic appliances and lighting, the other uses are water heating (13%) and cooking (5%).
[3] This ratio is based on the difference in energy efficiency rating between an "A+++" labelled refrigerator and a "D" rated appliance.
[4] http://www.muredatabase.org/aboutmure.html

Evidence from the EU however suggests that these policy efforts may not be sufficient. A midway assessment has revealed that the EU was only to reach half of his objective of a 20% reduction in primary energy demand unless additional efforts are made (European Commission, 2011b). This calls for the reinforcement of existing instruments and/or the introduction of new ones. In October 2012, the European Commission adopted a new Directive on Energy Efficiency with provisions for both end-use sectors and energy supply (European Commission, 2012), requiring Member States to establish national energy efficiency schemes and to put more emphasis on increasing energy efficiency in buildings. In the case of domestic appliances, increasing their average energy efficiency could reduce substantially residential energy consumption because consumers have the choice between appliances with very different energy efficiency levels.

It is often argued that these policies should mitigate two market failures (Allcott and Greenstone, 2012): imperfect information on energy performance and cognitive constraints on one side; and negative externalities on the other.

Imperfect information arises because energy efficiency is not directly observable by the buyer at the time of purchase. As such, the lack of information on energy costs could hinder consumers' evaluation of the energy costs of domestic appliances. Therefore, informing consumers about energy efficiency and energy savings constitutes a necessary step to market transformation. However, even when consumers can access information, it is often argued that they do not compute the expected and discounted energy savings of their energy efficiency investments in a perfectly rational manner. Other cognitive constraints would lead informed consumers to undervalue energy costs. The externality problem is more general: energy production and use generate health and environmental costs which needs to be properly internalized in energy prices.

The first paper of this PhD dissertation evaluates how energy efficiency of appliances is affected by energy prices. It tests if consumers' purchases of energy efficient appliances under-react to an energy price increase, principally because they would be myopic. To do so, we perform an econometric analysis on sales data of the UK market for refrigerators between 2002 and 2007, at a time when the EU Energy Label was already a mature policy and consumers knew about the energy consumption of the products that they were buying.

Since the 1980s, many scholars and policy-makers have argued that an "energy efficiency gap" could exist (Jaffe and Stavins, 1994), meaning that privately profitable investments in energy efficiency were not performed in practice by households and firms. The indication of an energy efficiency gap had been provided by various empirical estimations of *implicit discount rates*, the rates consumers and firms would be applying when purchasing energy-using products to weigh up future energy costs. Estimates reported for refrigerators ranged from 39% to 300% (Revelt and Train, 1998; Hwang et al., 1994; McRae, 1985; Meier and Whittier, 1983; Gately, 1980; Cole and Fuller, 1980); for air conditioners between 19% to 77% (Matsumoto, 2012; Train and Atherton, 1995; Hausman, 1979; Kooreman, 1995); and for water heaters between 67% and 84% (Hwang et al., 1994; Goett and McFadden, 1982).

Various reasons have been given to the energy efficiency gap in the case of appliances. The most frequently cited market failure is consumers' lack of information about energy efficiency or consumptions leading them to undervalue energy costs. In this respect, Newell, Jaffe, and Stavins (1999) show that the provision of information to consumers has an impact on consumers' sensibility to energy prices at the moment of purchasing room air conditioners and water heaters: informing consumers would therefore contribute to rationalize their choices towards more energy efficient products.

From a methodological perspective, the estimations of the implicit discount rate cited above have been made on a cross-section of products, by comparing their purchase price to their expected future energy costs while controlling for other observed product features. The major drawback of such estimations is that they cannot control for unobserved differences in the products that could be correlated with energy efficiency. Would there be such unobservables, the estimates of the implicit discount rates with such methods would be biased.

Panel data methods can control for time-invariant unobservables by construction. Allcott and Wozny (2011), Sallee, West, and Fan (2011) and Busse, Knittel, and Zettelmeyer (2012) have applied such methods on data from the automobile market and found that consumers' myopia could be much smaller than previously estimated. However, all these contributions have been conducted on cars, which is a relatively complex good to analyse. In particular, consumers can adapt their gasoline consumption to prices and these authors must therefore rely on assumptions regarding consumer use of cars to properly evaluate the energy efficiency gap.

With our data and a panel data econometric method, we find that there is an energy efficiency gap, as consumers would underestimate energy costs by about 35%. However, like in the studies on the automobile market, this energy efficiency gap is much smaller than what was previously estimated. The corresponding implicit discount rate that we find is around 8.7%.

Furthermore, we are able to quantify the impact of another mechanism that could widen the energy efficiency gap. Our econometric setting allows us to analyse both demand responses to energy price shocks and supply responses. We find that suppliers almost completely absorb energy price shocks by reducing more the price of energy inefficient appliances than the price of energy efficient ones. This asymmetric price response obviously reduces the consumer benefit of swapping for energy-efficient refrigerators. In the short run, almost all the energy savings from demand-side adjustments are compensated for. This is only in the long run that electricity price increases lead to energy savings as manufacturers progressively adapt to higher energy prices by launching new, more energy efficient products.

The second chapter of this PhD dissertation is a policy note that was part of a larger report for the French Agency of Environment and Energy Management. It looks at the main information-based policy that applies to domestic appliances in the EU: the EU energy label. Launched in 1995, the EU Energy Label makes compulsory the presentation of energy efficiency and energy use features on each appliance sold on the market. Whereas suppliers must provide a standardized energy label to dealers, the latter must put the label on a visible part of each appliance they sell. On the label, appliances have been ranked on a coloured scale from A+++ (very efficient) to G (very inefficient) making the identification of energy efficient appliances much simpler for consumers. The starting point of this chapter is that the EU Energy Label has become increasingly popular and today's consumers can know about the energy efficiency of main appliances when purchasing a new one in the EU. However, our analysis suggests that the effectiveness of the EU energy label does not solely depend on popularity, but on a list of key factors of success, including primarily that promised energy savings on the labels correspond to real energy consumptions. We conclude with suggesting indicators for policy-makers to monitor the Energy Label, and encourage them to intensify the controls on the accuracy of the energy label with the effective energy consumption of sold appliances.

The Impacts of Climate Change on Energy Investment Behaviour

Energy-related investments have more often been studied for their potential for climate change mitigation than for their relevance for adaptation. However, energy systems are sensitive to climate constraints and global warming may substantially affect local conditions of energy production and use. For example, the cooling of conventional and nuclear power plants may become problematic if river waters are warmer (IPCC, 2007). In the residential sector, energy is principally used for space heating and air-conditioning. Households will therefore necessarily adapt their energy consumption to any change in climate. The use of air-conditioning to adapt to excessive heat in summer would increase. In this context, energy consumption could rise in some regions due to global warming (for example electricity in California, as studied by Auffhammer and Aroonruengsawat, 2011).

Chapter 3 is a policy paper that investigates to what extent current investors take into account future climate change in their long-run investment decisions. Based on a review of the existing literature, we draw the list of the various parameters that will affect electricity transmission and generation before presenting the decision-making tools currently available that could be used by the electric sector in the perspective of adaptation to climate change. Our literature review suggests that decision-making tools are available to investors to properly account for climate change in their long-run investment decisions. Therefore, their effective use mostly depends on increasing investors' awareness on the potential impact of climate change on the energy system.

Furthermore, we argue that a better understanding of consumer attitudes towards weatherization is particularly relevant to understand climate change adaptation and its impacts.

Chapter 4 is an academic paper which studies the effect of household adaptation to climate change on residential gas and electricity consumption. Our research is based on data from 14 waves of the American Housing Survey (1985-2011) that have been matched with temperature and precipitation data from the National Oceanographic and Atmospheric

Administration covering 159 areas in the US. We adopt a two-stage approach. In the first stage, we assess long run adaptations by analysing how sensitive household decisions to perform home improvements are in relation to climate change. In the second stage, we run econometric equations of individual electricity and gas consumptions in which we take into account the likely changes in housing resulting from climate change.

The results of the econometric analysis suggest that adaptation to climate change from households will shift demand from gas to electricity. This is likely to be due to the increased need for air-conditioning, but also to the reduced use of gas heaters. In a simulation of residential energy demand, we predict that overall energy demand should decrease by 1.9% in the US assuming a 1°F inland average temperature increase. However, because electricity is more carbon-intensive that gas, GHG emissions could increase slightly due to adaptation to climate change if current methods of generation were used to produce electricity. We therefore conclude that the shift from gas to electricity resulting from climate change in residential housing constitutes an additional motivation for reducing the carbon footprint of US electricity.

Compared to other sectors, agriculture and food supply in particular, adaptation in the residential sector has been much less studied. Deschênes and Greenstone (2011) and Auffhammer and Aroonruengsawat (2011) have shown that electricity demand should be rising in the US due to climate change. They claim that this would be due to an increased utilisation of air-conditioning in summer. However, these two studies focus on the correlation between changes in temperatures and changes in energy consumption, and therefore do not directly look at the adaptations of the housing stock (including air-conditioning) that may lead to higher electricity consumptions. Even though air-conditioning is likely to be the main reason that explain a surge in electricity use (Sailor and Pavlova, 2003), it is unclear if the increase in electricity demand would be caused by the installation of new air-conditioners or the more intensive use of the existing ones. Furthermore, air-conditioning is not the only adaptation measure available to households that could lead to an increase in electricity demand: consumer may also prefer to install electric heaters instead of gas heaters if temperatures increase. Their operating costs are higher but their installation is cheaper, so that they fit well in regions in which heating needs are moderate (Mansur, Mendelsohn and Morrison, 2008).

The main contribution of chapter 4 is exploring the reasons behind the relationship between climate and energy use. We control for three types of investments in housing (major heating and air-conditioning equipment; energy integrity; and other home improvements) and distinguish between the changes in energy consumption imputable to changes in intensity in use and the ones imputable to adaptations of the housing stock. We find that the decrease in the use of gas would very likely be due to changes in the equipment installed whereas the more intensive use of already installed air-conditioners could drive electricity consumption upwards on its own. To our knowledge, Chapter 4 constitutes the first attempt to assess both long run adaptation and short run responses in terms of energy demand to evaluate the impact of household adaptation on energy use and GHG emissions from residential energy consumption.

In the end, the findings of the second part of this PhD dissertation are that increasing awareness about the potential impacts of climate change on the energy system is necessary for both suppliers and consumers of energy. In particular, various climate change adaptation strategies may exist, some putting more stress on the energy system (e.g. air-conditioning in the residential sector) than others (e.g. insulation). Our recommendation to policy-makers is that they encourage adaptations that can levy the burden that climate change will put on energy production and use, but also that they anticipate a higher demand for electricity and reduce the carbon footprint of its generation.

PART I. Investing in Energy Efficiency for Climate Change Mitigation: the Case of Domestic Appliances

Chapter 1. The Impact of Energy Prices on Energy Efficiency: Evidence from the UK Refrigerator Market

François Cohen, Matthieu Glachant, and Magnus Söderberg

Abstract

We use product-level panel data describing the UK refrigerator market from 2002 to 2007 to measure the impact of energy prices on energy use. The analysis deals with both demand-side and supply-side adjustments occurring in the market when the electricity price increases. That is, the short term response of consumers who modify their purchase behavior; the mid-term response of manufacturers/retailers which revise their price, and the long-term response of manufacturers which change product characteristics. We find a modest long-term elasticity of -0.09. This is driven by two inefficiencies. First, consumers undervalue the savings from energy efficient refrigerators by 35%. This means a moderate consumer myopia as the implicit discount rate is 8.7%. Second, nearly two-third of the increase in energy costs (almost all the costs as perceived by consumers) is compensated for by suppliers through relatively larger price reductions of highly energy consuming products in the mid-term. This finding calls for moving attention in the energy efficiency debate to the pricing behavior of manufacturers of durables.

Keywords: Energy Efficiency, Consumer Myopia, Energy Prices.

JEL Codes: D12, L68, Q41.

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Résumé du chapitre 1 en français

A partir de données de panel qui décrivent les produits vendus sur le marché des réfrigérateurs entre 2002 et 2007, nous mesurons l’impact des prix de l’électricité sur la consommation électrique des produits. Cette analyse prend en compte tant les ajustements de la demande que ceux de l’offre qui se produisent sur le marché lorsque les prix de l’électricité augmentent. Nous évaluons ainsi la réponse à court terme des consommateurs qui modifient leurs comportements d’achat ; la réponse à moyen terme des producteurs/revendeurs qui révisent leurs prix ; et la réponse à long terme des fabricants qui modifient les caractéristiques des produits vendus. Nous trouvons une élasticité modeste de -0.09 à long terme. Ce résultat est l’effet de deux défaillances. Premièrement, les consommateurs sous-estiment de 35% les économies d’énergie des réfrigérateurs efficaces sur le plan énergétique. Cela signifie qu’ils ont un comportement d’achat favorisant modérément le court terme, correspondant à un taux d’actualisation implicite de 8.7%. Parallèlement, un peu moins des deux-tiers des hausses des coûts d’utilisation des appareils (presque l’intégralité des coûts tels que perçus par les consommateurs) sont compensées par des réductions de prix plus importantes sur les produits les moins efficaces à moyen terme. Ce résultat encourage à prêter plus attention aux stratégies de prix des fabricants et des vendeurs de biens durables dans le cadre du débat sur l’amélioration de l’efficacité énergétique des produits utilisés par les consommateurs.

1. Introduction

In policy circles, it is common to believe that there exists an "energy efficiency gap" between the socially optimal level of energy consumption and observed consumption. At the international level, the International Energy Agency has been particularly active in disseminating this idea (see for instance, IEA, 2007, Ryan et al., 2011). Since a seminal paper by Hausman (1979) and the discussion of possible policy implications by Jaffe and Stavins (1994), it has also attracted considerable interest in the academic literature as shown in the recent survey by Gillinghan and Palmer (2014).

As explained by Allcott and Greenstone (2012), there are two potential reasons why public intervention can improve social welfare in this area. The first is the classical externality problem: the production and consumption of energy, in particular of fossil fuels, generate major environmental and health externalities which could be mitigated by policies promoting energy conservation. The second is due to imperfect information and other cognitive constraints that could lead economic agents to discard privately profitable investments that may limit energy use, in particular households and small businesses that have limited time and resources to evaluate infrequent decisions. Allcott and Greenstone (2012) refer to the latter type of failures as "investment inefficiencies".[5] They are particularly intriguing as they suggest the existence of win-win options entailing both economic and environmental benefits. In practice, energy efficiency choices fundamentally involve decisions that trade off an upfront cost – the purchase of an energy-efficient refrigerator, a fuel efficient car, the installation of insulation – and a stream of uncertain and future benefits induced by lower energy consumption. The choice is then inefficient if, in the eyes of an external observer, the decision maker gives non-optimal weight to the upfront cost relative to future energy costs. If the decision maker gives too high weight to the upfront cost, s/he is myopic or, expressed differently, the implicit discount rate used to calculate the net present value of the investment is too high.

The potential existence of investment inefficiencies has important policy implications (Allcott and Greenstone, 2012; Gillingham and Palmer, 2014; Verboven, 2002, Li et al., 2009). The most important one is that energy price increases induced by energy taxation and other instruments like emissions trading are likely to have limited impacts on residential

[5] The nature of the underlying causes of investment inefficiencies is extensively discussed by Gillingham and Palmer (2014).

energy use if households underestimate the size of future energy costs. Accordingly, they constitute a major justification for numerous real-world policies that target the market of energy-using durables such as investment subsidies that encourage the purchase of water heaters and the installation of insulation in dwellings and regulatory standards mandating a minimal level of energy or environmental performances of new motor vehicles like the EURO norms in Europe or the US-equivalent CAFE standards, building energy codes... They also plead in favor of energy labeling to improve consumer information.

The starting point of the present paper is the observation that the academic literature on the energy efficiency gap mostly concentrates on consumer behavior as illustrated by the recent review by Allcott and Greenstone (2012) and Gillinghan and Palmer (2014)[6]. We believe, and we will actually show, that what occurs on the supply side of the markets of energy-using durables is equally important. Consider, for concreteness, the case of refrigerators which will be studied in this paper. An increase in energy price reduces consumer utility and thus induces a negative shock on demand in the refrigerator market. In that case, the theory of industrial organization predicts that suppliers (manufacturers and/or retailers) will adjust their prices. More precisely, as refrigerators are differentiated goods, the price of models with poor energy performance is expected to decrease, while that of energy-efficient models will decrease less or can even increase if the total demand for refrigerators is sufficiently inelastic. Importantly, the fact that this price response is asymmetric – producers subsidize inefficient models in relative terms – damages energy efficiency as it reduces consumer incentives to shift to efficient models. This is not the end of the story, though; producers will also modify their product offer by launching new energy efficient models and withdrawing inefficient ones. A full understanding of the impact of energy prices on energy use requires taking into account all these adjustments.

In this paper, we use product-level panel data describing the UK refrigerator market from 2002 to 2007 to measure the impact of energy prices on energy use of sold appliances. Our distinctive contribution is to analyze the entire sequence of adjustments. We thus provide answers to three questions: On the demand-side, how large are investment inefficiencies? On the supply side, how large are refrigerator price adjustments when the electricity price changes? And how large are adjustments of product offers? By answering these questions

[6] A remarkable exception is a theoretical analysis by Fischer (2005) who stresses the importance of the supply side factors (including innovation) when designing policy to promote energy efficiency of household appliances.

and measuring the different impacts, we will also be able to assess the importance of investment inefficiencies relative to supply-side issues.

Methodologically, we develop a very simple discrete choice with differentiated quality à la Berry (1994) to describe demand and rely on first-difference panel data methods that allow us to control for time-invariant unobserved product attributes. We also control for product segmentation caused by product differentiation with a nested logit framework and address endogeneity concerns arising from refrigerators' prices and quantities being simultaneously determined. Price and product offer adjustments responses are estimated using reduced-form equations which impose less restrictions on how competition operates in this market. More specifically, we use first differences to estimate the impact of electricity price shocks on retail prices. To estimate how product offer is influenced by electricity prices, we take advantage of the fact that we observe in the data when a given model enters the market and when it exits (in the case where this occurs over the study period 2002-2007). We then estimate a dynamic fixed effect probit model by using the method of Wooldridge (2005).

Refrigerators constitute a suitable case to explore these questions, in particular compared to motor vehicles which have recently been the subject of a lot of research on the impact of gasoline prices (e.g., Allcott and Wozny, 2014; Busse et al., 2013, Anderson et al., 2013). To start with, consumers cannot adjust energy consumption after purchase contrary to car drivers who choose how much they will drive.[7] As a result, future energy consumption is exogenously determined by the characteristics of the product. This suppresses an important source of biases and of measurement errors. A second advantage is that there is no market for used cold appliances. This is obviously not the case for cars and empirical analysis therefore needs to develop complex solutions and/or make several assumptions to deal with this issue. See for instance Li et al. (2009) or Allcott and Wozny (2013) who only examine the impact of gasoline prices on the second-hand market. Third, the product is simple compared to cars and less subject to subjective feelings. This is a major benefit as dealing with taste shocks and unobserved product characteristics, that tend to be correlated with energy performance, is a major methodological difficulty. Note also that energy labelling is mandatory since 1995 for all refrigerators sold in the European Union, meaning that information asymmetry on energy performance is partly mitigated.

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[7] A consequence is that there is no "rebound effect" in this case. The work by Sallee, West, and Fan (2009) is an example of effective efforts to circumvent that problem with controls for odometer readings.

In our base specification, we estimate that consumers underestimate future energy savings by 35%. Even though this clearly indicates investment inefficiencies, their size is reasonable as it implies an implicit discount rate of 8.7%. There are several methodological reasons why our implicit discount rate is lower compared to what has been reported previously (from 39% to 300%, see the literature review in Section 2). The most important one is that we rely on panel data that allows better controls of unobserved product characteristics. In this respect, when using a hedonic pricing model on a cross section of models, the approach adopted by Hausman for instance (1979), we find a discount rate of 72%. Recent studies on cars using panel data also find rates of magnitude similar to ours (for instance, see Allcott and Wozny, 2014).

But as argued before, the most significant contribution of the paper is to estimate both demand- and supply-side effects. We confirm the theoretical prediction of an asymmetric price response to electricity price increases with producers decrease less the price of energy-inefficient models than that of efficient models. We also find a significant impact of electricity prices on the probability for a given model to be supplied in the market.

We are then able to calculate the relative size of the different demand and supply adjustments. More precisely, we use our estimates to simulate the impact of an increase in electricity price on the average annual electricity consumption of sold appliances. The simulation includes three stages: first, we predict the impact of electricity price shocks on purchasing decisions, holding the purchase price and the set of products available in the market constant. Second, we predict the impact of electricity price increases on the refrigerator purchase prices and adjust market shares accordingly. Third, we correct the market shares of commercialized products according to their probability of being commercialized, which we estimate with our probit model on product offer.

We find that, holding constant the supply behaviour, a 10% electricity price increase on demand induces a 3.2% decrease in energy use. In the second stage, price adjustments lead to almost cancel this impact – reduction falls down to 0.04% - as producers cushion the impact of electricity price changes by subsidizing selectively the least efficient products. Note that this effect would not occur if the refrigerator market was perfectly competitive. Under perfect competition, prices are equal to marginal production costs, implying zero price adjustments if marginal costs are constant, which sounds a reasonable assumption as our scenario does modify drastically the quantities produced. In the third stage, producers however partly compensate this impact by offering more energy-efficient models in the market, leading to a long-term reduction of energy use of 0.9%.

What lessons can be drawn from these figures? To start with, the inefficiencies due to consumer myopia and imperfect competition are far from being negligible: in the absence of consumer myopia and price adjustments, the long run reduction would be 7.1%, that is, seven times larger. We also able calculate the size of each inefficiency by simulating a scenario where only one of each is present. The simulation shows that imperfect competition reduces more the effectiveness of energy price increases than myopia: The long term impact of energy use would -1.5% if consumers were perfectly rational under perfect competition while it would be – 4.5% with myopic consumers under imperfect competition. Supply-side issues cannot be ignored when analysing the links between energy efficiency and energy prices.

As inefficiencies are sizeable, this calls for complementing policy solutions based on energy price changes (e.g., energy taxation) with other instruments. The focus on demand is then clearly not sufficient when designing the policy mix. As an illustration, energy labelling can constitute a (partial) solution to demand-side failures, but it does not mitigate the asymmetric pricing problem. It can even exacerbate it as producers have more incentives to subsidize inefficient models if consumers pay more attention to energy efficiency. Going further by evaluating the welfare properties of the different policy options is clearly beyond the scope of this paper, in particular because we use reduced-form supply equations. In any case, our results suggest that focusing on demand behavior and consumer surplus is not sufficient to derive robust policy recommendations.

The rest of this paper is structured as follows. In the following section, we briefly review the literature. In Section 3, we develop a conceptual framework and address identification issues. Section 4 presents the data. We then present and interpret the estimated results in the following section. In Section 6, we run simulations to predict the impacts of a 10% increase of the price of electricity. In Section 7 we summarize our findings and formulate policy implications.

2. Related literature

The empirical literature on the impact of energy prices on energy efficiency is well developed. To the best of our knowledge, there exists however no work which studies the impact of energy price changes on the entire sequence of demand and supply responses (quantity, price, and innovation).

As explained above, the majority of the papers focus on demand and consumer myopia. Following the work of Hausman (1979) on room air conditioners, earlier research found implicit discount rates that are substantially larger than real financial discount rates. In the case of electric appliances, rates reported for refrigerators range from 39% to 300% (Revelt and Train, 1998; Hwang et al., 1994; McRae, 1985; Meier and Whittier, 1983; Gately, 1980; Cole and Fuller, 1980); for air conditioners between 19% to 77% (Matsumoto, 2012; Train and Atherton, 1995; Hausman, 1979; Kooreman, 1995); and for water heaters between 67% and 84% (Hwang et al., 1994; Goett and McFadden, 1982).

Most recent works lead to revise downward these estimates. For refrigerators, Tsvetanov and Segerson (2014) find discount rates in the range 13-22% in a paper which looks at the impact on consumer surplus of energy labeling. The same pattern is found in recent papers dealing with gasoline prices and fuel efficiency. Allcott and Wozny (2014) whose methodological approach is similar to ours find a discount rate of 16%; Busse et al. (2013) produce several estimates under different assumptions, none of these exceed 20% and many are close to zero. The same pattern is found by Goldberg (1998). As evoked above, the main difference between these new results and the earlier literature is the use of panel data which allows controlling some of the unobserved product characteristics that tend to be correlated with energy performance.

A few papers look both at price and quantity adjustments. An example is the recent paper by Houde (2014a) on the producer and consumer response to energy labeling in the US refrigerator market. Busse et al. (2013)'s work on the car market examine both the level of the discount rate and the price response of car manufacturers and retailers to gasoline price changes. Interestingly, they show that the price adjustment is much higher in the used car market than in the market for new cars. Verboven (2002) is primarily concerned by the pricing behavior of car manufacturers.

Finally, there is a significant literature looking specifically at the impact of energy prices on innovation. A good example is the work by Jaffe et al. (1999) on energy-using consumer durables or by Popp (2002).

Why is it then useful to combine the study of all adjustments as we do in this paper? The answer is very simple: it allows an assessment of the relative importance of the different issues. Among other things, it then shows that the usual focus on demand and consumer myopia is far too partial to get a full understanding on how energy prices influence energy use and the policy solutions that can be introduced to complement energy taxation.

3. Conceptual framework

A simple model

To begin with, we develop a simple discrete choice model of the refrigerator market derived from Berry (1994) to describe demand. There are *T* markets, each representing the UK refrigerator market during year *t* (with *t* = 1,…,*T*). For each market, we observe aggregate quantities sold, average prices, and product characteristics for *J* models of refrigerators.

Consumers choose the product that maximizes utility. The indirect utility function of consumer *i* purchasing a new refrigerator *j* in year *t* is equal to $U_{ijt} = V_{jt} + \epsilon_{ijt}$ where V_{jt} is the average utility and ϵ_{ijt} is consumer *i*'s unobserved heterogeneity that captures deviation from the average. The average utility[8] is:

$$V_{jt} = u_{jt} - \alpha\left(p_{jt} + \gamma C_{jt}\right)$$

In this expression, u_{jt} captures the value of usage of the refrigerator *j* over its lifetime which depends on product characteristics such as size, whether the fridge is built-in or freestanding. p_{jt} is its purchase price, C_{jt} is the discounted electricity cost of the product. C_{jt} has a negative impact on V_{jt} which is proportional to α, the marginal utility of money, and a parameter γ, which captures consumers' perceptions about energy costs. If they are perfectly rational, we have $\gamma = 1$. If myopic, it is expected that they underestimate the disutility from energy costs so that $\gamma < 1$. Estimating this parameter is one crucial objective of the paper.[9]

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[8] This form of the indirect utility can be derived from a quasilinear utility function, which is free of wealth effects. This is a reasonable assumption for refrigerators, which usually represents a tiny share of individual income.

[9] Here, the modeling strategy is to adopt the standard rational choice model, except but the parameter γ. An alternative approach could be to adopt a behavioral economics framework, but this will prevent the measurement of efficiency gap, which is just exactly the gap between actual behavior and perfect rationality. This approach is for example developed by Segerson and Tsvetanov (2014).

Next we decompose the value of usage in two additively separable terms: $u_{jt} = u_j + \xi_{jt}$ where ξ_{jt} captures the time-varying component of the valuation of observed and unobserved product characteristics. Hence, we have:

$$V_{jt} = u_j - \alpha\left(p_{jt} + \gamma C_{jt}\right) + \xi_{jt}$$

Berry (1994) generalises McFadden's (1973)'s discrete-choice demand model by transforming the logit model into a linear model that can be estimated with market-level data. In Berry's framework the probability good *j* is purchased asymptotically corresponds to its market share at time *t*. Hence:

$$s_{jt} \equiv \frac{e^{V_{jt}}}{\sum_{k \neq j} e^{V_{kt}}}$$

A consumer can also choose an outside option indexed 0 that consists in purchasing no refrigerator. Normalizing its utility V_{i0t} to zero, the market share of product *j* at time *t* can be compared with the market share of the outside good so that $s_{jt}/s_{0t} = e^{V_{jt}}$. In logs, this simplifies to $\ln\left(s_{jt}\right) - \ln(s_{0t}) = V_{jt}$. The problem is that this equation rests on the hypothesis of irrelevance of independent alternatives (IIA) which generate implausible substitution patterns in segmented markets.

To relax this assumption, we adopt a nested logit framework in which consumers' idiosyncratic preferences are correlated across refrigerators within the same "nest" (Corr($\epsilon_{ijt}, \epsilon_{ikt}$) $\neq 0$), and zero otherwise[10]. The mutually exclusive nests are specified *ex ante* by grouping together products the analysist thinks are closer substitutes. Under these assumptions, Berry shows that:

$$\ln\left(s_{jt}\right) = u_j - \alpha\left(p_{jt} + \gamma C_{jt}\right) + \sigma \ln\left(s_{j(g)t}\right) + \ln(s_{0t}) + \xi_{jt} \tag{1.1}$$

[10] Goldberg (1995) and Allcott and Wozny (2014) are other examples where the nested logit model is used. A popular alternative is the random coefficient models. We believe the nested logit model is a good option here for several reasons. To start with, random coefficients cannot be eliminated through first-differencing we use in the subsequent analysis to control for unobserved quality and cost characteristics and the outside option. That means we would need to estimate a non-linear equation and we could not ignore the outside option, of which quantification is difficult and subject to measurement errors.

where $s_{j(g)t}$ is the market share of product j as a fraction of the total sales within group g that includes product j and $\sigma \in [0,1]$ is a scalar which parameterizes the within-nest correlations. Note that, we get a standard logit equation if $\sigma = 0$.

In our specification, we construct the product groups based on two dimensions that create product segmentation in the refrigerator market: a binary capacity indicator (i.e. the refrigerator capacity is below or above the sample median capacity) and whether the appliance is a refrigerator or a combined refrigerator-freezer. This choice is based on a judgment of the degree of substitutability of different products. In this respect, we believe that consumers willing to purchase a refrigerator, unfortunately not available, are unlikely to go for a combined refrigerator-freezer instead. Similarly, the choice of the size is strongly influenced by family characteristics (size, food consumption habits…) and dwelling characteristics. In Appendix A1, we give results with alternative nest structures.

We now turn to the specification of the discounted lifetime electricity cost C_{jt}. The attention parameter γ is inserted in Eq. (1.1) to capture potential behavioural failures. As a consequence, C_{jt} should not be viewed as representing the valuation of the electricity cost by real-world consumers. It is the cost they would consider if fully rational. They would then calculate the net present value of the electricity cost with the standard formula:

$$C_{jt} = \Gamma_j \times \sum_{s=1}^{L_j} \frac{q_{t+s}^{f}}{(1+r)^s} \tag{1.2}$$

In this equation, L_j is product *j*'s lifetime, Γ_j is the level of energy consumption per time period, q_{t+s}^{f} is the electricity price at time $t+s$ that is forecasted at the time of purchase t and r is the discount rate. Note that forecasted electricity prices are unobserved as the data only include *actual* prices.

Recall that the calculation of C_{jt} is based on strong rationality assumptions. Accordingly, Γ_j and L_j are product energy consumption and lifetime evaluated by experts which are assumed to be perfectly known by the consumer, r is the privately-rational discount rate. In the following, we will use the discount rate offered in financial markets in year *t* (the bond deposit rate). Finally, q_{t+s}^{f} is the future electricity prise estimated with a sophisticated forecasting model.

In this latter respect, we consider that a perfectly rational consumer makes an educated guess about future electricity prices based on the entire series of past prices. We construct this guess by applying an autoregressive integrated moving-average model (ARIMA) on monthly data on real electricity prices.[11] ARIMA models are frequently applied in time-series econometrics to generate forecasts. This technique allows us to recreate the entire flow of future expected electricity prices that enter Eq. (2.2).

The best fit with our data is obtained with an ARIMA process with one lag for the autoregressive term and one lag for the moving-average term:

$$q_t = a + bq_{t-1} + c\vartheta_{t-1} + \vartheta_t$$

where a, b and c are parameters and ϑ_t is the error term at time t. The model can be used recurrently to make forecasts, using the predictions of the previous periods to make new predictions. We therefore run as many models as we have years covered with our data in line with the assumption of rational expectations. We then calculate the forecasted prices with the formula:

$$q_{t+s}^{f} = \hat{a}_t + \hat{b}_t q_{t+s-1}^{f} \tag{1.3}$$

where $\hat{a}_t$ and $\hat{b}_t$ are estimates of a and b using all the data available on electricity prices up to time *t*.

The demand equation is specified by combining (1.1), (1.2) and (1.3). To derive an econometric specification for sales, we add year dummies τ_t to (1.1) and then take the first-differences in order to absorb the share of the outside option, the value of usage and any shift in the overall market share level. This leads to:

$$\Delta\ln(s_{jt}) = -\alpha\left(\Delta p_{jt} + \gamma\Delta C_{jt}(r)\right) + \sigma\,\Delta\ln(s_{j(g)t}) + \Delta\tau_t + \Delta\xi_{jt} \tag{1.4}$$

where Δ is the first-difference operator and ξ_{jt} is now the econometric error term capturing unobserved time- and product-varying heterogeneity.

[11] In a recent paper, Anderson et al.(2013) show that US consumers tend to believe that gasoline prices follow a random walk, so that the current price is a martingale. Again, we do not specify C_{jt} to capture real-world expectations, so that we should not use a no-change forecast even if this belief also applies to UK electricity prices. We do however provide the results in Appendix under this alternative assumption as a robustness check. This leads to increase the size of γ (and thus to reduce myopia).

Price

In contrast with the demand equation, we rely on a reduced form equation to describe refrigerator price adjustments induced by electricity price changes. Developing a structural approach to describe the supply would require taking into account both pricing and product innovation behaviour of multi-product firms. We would thus need to introduce multiple assumptions on how competition works. Reduced form equations impose much less restrictions.

Recall that our interest is in the influence of electricity costs. Accordingly, our price equation[12] is:

$$p_{jt} = \beta - \eta C_{jt} + \theta X_{jt} + \tau_t + \mu_j + \epsilon_{j,t} \qquad (1.5)$$

where X_{jt} is a vector of control variables to be described below. τ_t and μ_j are year dummies and product fixed effects, respectively. Our objective here is to estimate η. Importantly, this parameter measures neither the characteristics of the demand curve nor those of the supply curve. Instead it estimates the impact of electricity costs on the equilibrium refrigerator price, once demand and supply responses are both taken into account, holding constant product offer. This estimate will thus allow deriving a mid-term elasticity after quantity and price adjustments.

Product offer

Turning next to product offer, we take advantage of the fact that the data describes the products sold in the market in year *t.* For many products, we thus observe when it has been launched and/or when it has been eventually withdrawn[13]. Again we expect an increase in electricity price would induce the launch of more energy-efficient models and the withdrawal of less efficient ones.

Let d_{jt}^* denote a binary variable indicating the availability of product *j* at time *t*. More specifically, $d_{jt}^* = 1$ if the product is on the market and zero otherwise. In addition, we

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[12] In a variant, we include both the electricity cost and its squared value to test for the existence of a non-monotonic relationship between product price and electricity costs. More specifically we could expect that energy price increases will decrease the price of the products consuming more energy while the price of energy-efficient models could increase if the total demand is inelastic. Results disconfirm this prediction; they are presented in Appendix A6.

[13] The dataset also includes products that are observed every year. That is, products that have been launched before 2002 and that have not been withdrawn before 2007.

define $d_{j,t}$ as the probability that product j is available at time t. We then use a dynamic probit equation which relates this probability to a set of explanatory variables:

$$d_{jt} = \Phi(k_d d^*_{jt-1} + k_p p_{jt} + \ k_c C_{jt} + \tau_t + \mu_j) \qquad (1.6)$$

$\Phi(.)$ is a cumulative normal function with zero mean and a variance equal to one and k_d, k_p and k_c are parameters. The two crucial variables are the purchase price p_{jt} and the operating cost C_{jt} which are both expected to decrease the dependent variable ($k_p, k_c < 0$). We adopt a dynamic specification with d^*_{jt-1} as an independent variable in order to control for path dependency: launching a product in the market is more costly than withdrawing it.

Identification issues

Sales

A concern with the sales equation (1.4) is that the purchase price p_{jt} is endogenous as quantities and prices are simultaneously determined in the market equilibrium. It implies that unobserved product characteristics that vary over time are correlated with prices: $[p\xi] \neq 0$. Or, to be precise, our problem is the time-varying *valuation* by consumers of product characteristics is correlated with the error term as the characteristics themselves are fixed. The log of the within-nest market share $\ln\left(s_{j(g)t}\right)$ is also endogenous: mathematically, a higher value of ξ causes more sales of refrigerator j and because this product belongs itself to nest g, an increase in s_{jt} mechanically imply increases in $s_{j(g)t}$.

The problem might not be too severe though as first differencing already controls for the correlation between prices and the linear component of product-specific unobserved quality that do not varies over time. As regards specifically the variable $\ln\left(s_{j(g)t}\right)$, the source of bias is further limited by the fact there are a large number of product-by-year combinations in each nest. An instrumental variable approach is nevertheless adopted. Another reason for doing so is to circumvent a potential measurement error problem with the dependent variable as we do not observe transaction prices but a national average transaction price calculated by GfK (see detail below)[14].

[14] This problem is likely to be less severe than in the auto market where list prices can widely diverge from the prices that are actually paid after commercial negotiations.

To construct the instruments, a classical approach takes advantage of the fact that the market is imperfectly competitive. It follows that characteristics of products $k \neq j$ influence p_{jt} but not the utility V_{jt}. Berry (1994) suggests using the nest structure of the model. His proposed instruments are then the averages for different product features within and/or out of the product group that product *j* belongs to. This approach is extended in Berry et al. (1995).[15] A weakness of this strategy is that taste shocks that affect the other products can also influence utility of product j. For instance, marketing efforts by a firm can induce a taste shock that will affect all its products. Or a given characteristics that concern several models might become popular among consumers. In this respect, the fact that refrigerators are quite standardized products, except in the dimensions we base the nests on, is not necessarily good news. That means that unobserved product characteristics are going to be correlated across nests and manufacturers. The underlying general problem is that we would ideally like to use variables that shift cost as they would be uncorrelated with the demand shock, but quality variables affect both utility and production costs.

Our solution is to use instruments based on the price of products sold in outside markets. We consider two markets: the upright freezer market (i.e. not the chest freezer market) and the washing machine market. Freezer and washing machines present two useful characteristics. First, they are sold outside the refrigerator market, and thus to different consumers. One can thus assume that taste shocks are less likely to be correlated. Second they share some technical similarities with refrigerators as they are all large household appliances. It follows that some shocks affecting production costs – e.g., an increase in steel price – can be correlated across markets.

In fact, we do not use directly the price of freezers and washing machines. This would produce too weak instruments for these two products differ significantly from refrigerators. Instead, we use the implicit price of two characteristics that also differentiate refrigerators: capacity and whether the appliance is built-in or freestanding. These implicit prices are estimated using a hedonic pricing model on product-level data for the UK freezer and washing machine markets between 2002 and 2007 obtained from GfK. The details are given in Appendix A2.

[15] They use the observed product characteristics (excluding price and other potentially endogenous variables), the sums of the values of the same characteristics of other products offered by that firm (if the firm produces more than one product), and the sums of the values of the same characteristics of products offered by other firms.

The price equation

We also express equation (1.5) in first differences:

$$\Delta p_{jt} = -\eta \Delta C_{jt} + \theta \Delta X_{jt} + \Delta \tau_t + \Delta \epsilon_{j,t} \tag{1.7}$$

In order to properly identify the parameter η, we need select the variables in the vector X_{jt} that control for supply and demand factors, except the electricity cost, that vary over time and across products. On the demand side, this is the utility component ξ that we have extensively discussed above. On the supply side, the main omitted variable is the time varying component of product j's production cost. The price is also influenced through competition by other product characteristics.

These considerations suggest using as regressors in (1.7) the instruments used in the sales equation. They are correlated with product j's characteristics and thus ξ and the production cost as argued before.

The product offer equation

For convenience, we rewrite the equation here:

$$d_{jt} = \Phi(k_d d^*_{jt-1} + k_p p_{jt} + \ k_c C_{jt} + \lambda_t + \theta_j) \tag{1.8}$$

We use the method suggested by Wooldridge (2005) to estimate this dynamic model. His method consists in re-expressing a dynamic fixed effect probit model into a random effect probit model than can be more easily computed. The correlation between the fixed effect θ_j and the initial value $d^*_{j,0}$ is made explicit. In our case, this gives:

$$\theta_j = k_0 + k_1 d^*_{j0} + k_z Z_j + \nu_j \tag{1.9}$$

Z_j is the row vector of all nonredundant explanatory variables in all time periods. It includes time-constant product features (e.g., size or energy efficiency rating) but also the purchase price of products at each time period (i.e., the price in 2002, in 2003...). To avoid multicollinearity, it however excludes year dummies and only includes the running cost for one year because they are calculated from Γ_j, which does not vary over time. k_0 and k_1 are parameters, k_z is a vector of parameters and ν_j is a random effect such that $\nu_j | (d^*_{j0}, Z_j)$ follows a normal distribution.

Combining (1.8) and (1.9) leads to a random-effect probit model except that d^*_{j0} and Z_j are included as explanatory variables:

$$d_{j,t} = \Phi\left(k_d d^*_{jt-1} + k_p p_{jt} + \ k_c C_{jt} + \lambda_t + k_0 + k_1 d^*_{j0} + k_z Z_j + \nu_j\right) \tag{1.10}$$

The estimation of (1.10) poses two problems. The first is that the information on p_{jt} is missing in the data for all the periods when product *j* is not available on the market ($d^*_{jt} = 0$). We thus need to make an assumption about the purchase price of this product in the years it is out of the market. The second problem is that the purchase price of appliances and the probability d_{jt} are simultaneously determined, implying that p_{jt} is endogenous.

We resolve these two problems as follows. For all the products that are not commercialised at time t, we need to make an assumption about their purchase price if they had been commercialised. The simplest method is to perform a regression on observed purchase prices (when $d^*_{jt} = 1$) and produce out-of-sample predictions for p_{jt} when $d^*_{jt} = 0$. However, this would underestimate the standard error of the estimated coefficients as we would be using imputed values for p_{jt} as if they were observed values

We alternatively perform multiple imputations for each missing p_{jt}. This technique allows calculating standard errors for the estimated parameters of the dynamic probit model that take into account the fact that prices are imputed when $d^*_{jt} = 0$. The process to create imputations is as follows. First, we look at the distribution of purchase prices p_{jt} and perform a transformation on p_{jt} so that the transformed purchase prices follow a normal distribution.[16] The transformation that we use is:

$$\tilde{p}_{jt} = \ln\left(\left[p_{jt}\right]^{n_0} - n_1\right) \tag{1.11}$$

$\tilde{p}_{jt}$ are transformed prices, n_0 and n_1 are parameters that ensure that the skewness of the distribution is close to 0 and its kurtosis around 3, which are two properties of normal distributions. Then, we run a fixed effect linear regression on transformed prices:

$$\tilde{p}_{jt} = h_j + h_c C_{jt} + h_W W_{jt} + h_t + x_{jt}$$

h_j is a product specific fixed effect, h_t a time dummy and h_c a parameter whereas x_{jt} is an error term. Importantly, W_{jt} corresponds to the vector of instruments that have been used to control for the sales-price endogeneity and h_W is a vector of parameters. Using these instruments in the imputation process allows us to control for the endogeneity on imputed

[16] The multiple imputation method that we describe is known to be biased if applied to non-normally distributed variables.

purchase prices. We denote $\hat{p}_{jt}$ the predictions that we obtain from this fixed effect linear regression.

Based on the results of the linear regression, we create ten imputed prices for each missing value of p_{jt}. If we denote *m* the imputation number, each imputed transformed price of product *j* at time *t* is given by:

$$\tilde{p}_{jt}^{m} = \hat{p}_{jt} + x_{jt}^{m}$$

where x_{jt}^{m} is a randomly assigned and normally distributed error term corresponding to imputation *m* for product *j* at time *t*. Next, we use equation (1.11) the other way round to calculate the value of the imputed prices p_{jt}^{m} from their transformations $\tilde{p}_{jt}^{m}$. This step allows obtaining imputed values $p_{j,t}^{m}$ which distribution is very similar to observed prices.

Once the values of p_{jt}^{m} have been obtained, we estimate the dynamic fixed effect probit model above as many times as there are imputations and then compute consistent coefficient values and standard errors that take into account the uncertainty surrounding the value of p_{jt} when $d_{jt}^{*} = 0$.

Note that the technique described above allows us to obtain consistent imputations that take into account the endogeneity of purchase prices. To control for the endogeneity of observed purchase prices, we run a linear regression similar from the above and extract predicted values that we use later on in the dynamic fixed effect probit model instead of using observed prices.

4. Data

We use market data from the refrigerator market in the UK on the product level from 2002 to 2007 collected by the market research company *GfK Retail and Technology* (received by the Department for Environment, Food and Rural Affairs). The data includes detailed annual information on refrigerators and combined refrigerators-freezers sold in the UK. We identify products by brand name and series numbers. If not available, we rely on available information on product features (width, height, total capacity, energy consumption, energy efficiency rating, freestanding/built-in feature, availability of no-frost system and availability of freezer).[17]

Each observation is a product *j* in year *t* with measures including number of units sold, average consumer price, a set of product features such as size, whether it is a simple refrigerator or a refrigerator-freezer, indication whether it has a separate freezing compartment that can store food at -18°C, and annual electricity consumption (details provided in Table 1.1). We do not have detailed information on product-specific lifetime in the *GfK* data. We thus use the information provided by the Association of Manufacturers of Domestic Appliances that estimates the lifetime to 12.8 years for refrigerators and to 17.5 years for combined refrigerators-freezers (AMDEA 2008).

Although the data is not used in our estimation, we also know the product's classification according to the EU energy label. Energy labelling is mandatory since 1995 for all refrigerators sold in the European Union. In our data, each product is assigned to a class from A++ (the most energy-efficient) to G (the least energy efficient). This rating does not capture the absolute energy consumption of the appliance, but its relative consumption in comparison with products providing the same cooling services.

Moreover, we drop observations with low sales. More specifically, we drop each model of which annual sales never exceeds 500 units over the study period[18]. This ensures that the models in the sample were actually commercialized at a large scale (not only on a few local markets) during at least one year over the period. We also drop every observation (product x year) with less than 10 units sold to avoid having models with sales near zero, creating a bias for estimating the discrete choice model.

[17] Brand name and series numbers were not available for retailers' own brands. For these products, identification is based on product features alone. This means that, with this method, two models from different retailers' brand but with exactly the same product features cannot be properly distinguished. Therefore, observations for retailers' brand appliances are dropped each time the same product features corresponds to various models of appliances for the same year. For products where brand name and series numbers are available, identification on product features is always necessary considering that manufacturers can change some of the product features of a model without changing the series number (there can be various versions of a same model of appliance).

[18] We reduce this threshold to 100 for the estimation of the dynamic fixed effect probit model though. Since we are interested in the appearance and disappearance of products in this specific case, using too high a threshold would then conduct us to overlook the appearance of some products on the market.

Summary statistics on product characteristics are displayed in Table 1.1. Table 1.2 provides an overview of the distribution of prices and market shares across energy efficiency classes. The initial data set includes 2,651 observations of which 1,823 are used to construct the first differences for the econometric estimation. The total number of differences used in the econometric estimation is thus 1,118. Descriptive statistics are provided for the 1,823 observations used to construct the differences of the estimation sample of the market share and price equations.

Table 1.1: Summary statistics on product characteristics

Variable	Unit	Mean	Std deviation
Annual sales, used for the log of market shares $\ln(s_{j,t})$	# of units	3283.0	5973.8
Purchase price, $p_{j,t}$	real £	343.6	230.9
Appliance lifetime, L_j	years	15.48	
Energy consumption, Γ_j	kWh/year	319.3	138.4
Height	cm	138.9	43.4
Width	cm	58.8	9.3
Capacity	litres	240.2	109.3
Energy efficiency rating[a]		2.51	0.87
Share of combined refrigerators-freezers		0.57	
Share of built-in appliances		0.18	
Share of appliances with no-frost system		0.23	

Notes. Source: GfK, provided by Defra. Survey years: 2002-2007. 1,823 observations. [a] To obtain a numeric value for the energy efficiency rating (from “G” to “A++”), ratings were recoded with “A+” set equal to 1, “A”=2 and so on up to “G”=8.

Table 1.1: Sales-weighted price and market share of appliances, breakdowns by energy efficiency class

Category	Sales-weighted average price	Market share
Energy efficiency rating		
A+	285.2	0.02%
A	270.8	1.94%
B	306.5	61.98%
C	219.9	22.10%
D	225.0	13.59%
E	107.6	0.27%
G	130.7	0.11%

Notes. Source: GfK, made available by Defra. Survey years: 2002-2007. 1,823 observations. No observation with energy efficiency rating of “F”.

We use the real average bond deposit rate of UK households of 2.83% as recorded by the UK Bank of England (2013) for 2002-2007 to discount the future electricity cost.[19] This cost is calculated using data on retail electricity price from the Department of Energy and Climate Change (2013). The real monthly electricity price data are expressed in pence with CPI=1 in 2005 (displayed in Figure 1.1).

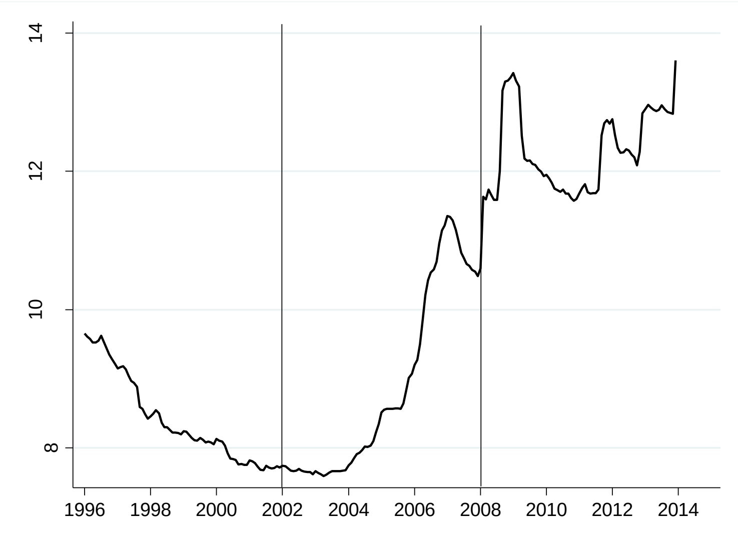

Figure 1.1: Average monthly electricity prices in the UK, 1996-2014

Note: The study period is between the two vertical lines

As explained in the model section, we use an ARIMA model to proxy rational expectations about energy prices. The best fit to our data is obtained using an ARIMA process with one lag for the autoregressive term and one lag for the moving average term. We run six models to produce different price expectations for each year available in the GfK data, from 2002 to 2007. Each ARIMA model is run with the electricity price data available from the previous years (e.g. the price expectations for consumers in 2003 are based on prices up until Dec. 2002). We then compute price expectations up to 2030 to be able to compute expected electricity costs entailed by appliances until their end-of-life. The detailed results of the ARIMA models are in Appendix (A9).

The initial data set includes 4,166 observations of which 2,706 are used to construct the first differences for the econometric estimation. The total number of differences used in the econometric estimation is thus 1,623. Descriptive statistics in Tables 1.1-2 are provided for

[19] The nominal rate was 4.61% and the Bank of England code for the statistics is IUMWTFA. We subtracted the average inflation rate of 1.78% between 2002 and 2007.

the 2,706 observations used to construct the differences of the estimation sample of the market share and price equations.

5. Results

Sales

Estimating the attention parameter is not straightforward as there is an interaction between α and γ. The standard empirical approach is to separately estimate the coefficients for the price and the energy costs in a linear setting, and deduce from it the values of α and γ. We prefer to use a GMM estimator to estimate directly all the model parameters and as this directly gives their confidence intervals. Table 1.3 reports estimation results of Equation (1.6). We include the results obtained with the alternative linear approach as a test of robustness in Appendix A3.

The nested structure of the model properly accounts for market segmentation, with $\sigma \approx 0.80$ (significant at 5% level). Additionally, the coefficient for the valuation of money has the expected sign and is different from 0.

The main result in Table 1.3 is the fact that $\gamma \approx 0.65$. The 95% confidence interval is 0.33-0.96. Hence the estimate of the attention parameter is statistically different from both 0 and 1, which means that consumers discount future energy costs too much but still take them into account when purchasing cold appliances. While consumers systematically underestimate energy costs they still take a large share (65%) of future discounted operating costs into consideration when purchasing a cold appliance. Another way of discussing this result is to compute the "implicit" discount rate which would rationalize consumer behavior. That is, the value of *r* necessary to obtain a value of γ equal to one. We show in Appendix A4 the implicit discount rate is 8.7%. Therefore, consumers behave as if they use a discount rate of 8.7% to compute the net present value of electricity cost.

This implicit discount rate is relatively low when we compare with the previous literature on refrigerators, which have found implicit discount rates above 30%. One explanation is that previous estimations of the implicit discount rate used older data. Since then, investment inefficiencies might have reduced because a policy now targets purchase decisions in the European Union: energy labelling is mandatory for refrigerators since 1995. Our result could indicate that this approach was quite successful. This is in line with the views expressed by many observers who consider that the EU Energy Label has been very successful in reducing the information gap about energy efficiency (see for example Atkins and ECN, 2006). Another possible explanation is methodological. We use panel data techniques which better control for unobserved product differences. In this respect, when using a hedonic pricing model on a cross section of models, the approach adopted by Hausman (1979) for instance, we find a discount rate of 72% (See in Appendix A5). As argued in Section 2, recent studies which rely on panel data find rates of similar magnitude.

The average effect obtained with this base specification is robust to changes in the parameters used to calibrate the GMM model: the sensitiveness analysis with different values of product lifetimes, electricity prices and choice for the nests presented in Appendix (A1, A6-8) show little differences in the magnitude of the implicit discount rate.

Table 1.2: First difference IV-GMM estimation results of the sales equation

Dependent variable	Logarithm of market share of product *j*
Importance of total electricity costs (γ)	0.6476*** (4)
Utility for money (α)	0.0075*** (3.55)
Within-group correlation of error term (σ) for the demand equation	0.7967*** (8.04)
Year dummies	Yes
Observations	1,118
Test of over-identifying restriction (p-value)	0.94

Notes. Three instruments are used. They correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines, and the squared value of these fixed effects for upright freezers . The nests on which σ is calculated distinguish refrigerators from combined refrigerators-freezers and appliance by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

Price

Estimation results are shown in Table 1.4. We also use the generalised method of moments to estimate this equation. As expected, producers adapt retail prices to the electricity costs: an increase by one pound in future electricity costs reduces the sales price of an appliance by 64 pence. Two third of the increase in future operating costs are therefore compensated for by a decrease in the purchase price of appliances.

Table 1.3: First difference GMM estimation results of the price equation

Dependent variables	(1)
Discounted electricity costs, η_1	-0.6405*** (-4.28)
Fixed-effect derived from the price of upright freezers (by size by year)	7.77* (1.77)
Squared	0.0376** (2.11)
Fixed-effect derived from the price of washing machines (by size by year)	171.19*** (3.76)
Year dummies	Yes
Observations	1,118

Notes. The price equation includes the instruments used in the market share equation as control variables for time-varying changes in production costs. *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

Product offer

Results for the dynamic fixed effect probit model are reported in Table 1.5. Unsurprisingly, there is high probability that a product is commercialised if it was on the market the year before: the coefficient is both high and strongly statistically significant. Conversely, a product available in 2002 is more likely to be obsolete in the future years and therefore to disappear during the period covered with our data.

More importantly, any increase in the electricity costs reduces the probability that the product is commercialised. We can therefore expect that highly energy consuming products – energy-inefficient products or big refrigerators - are more likely to exit the market when electricity prices increase.

Likewise, products with too high a sales price tend not to be commercialised. This result is statistically significant at 1%. Conversely, any reduction in the purchase price of an appliance increases its probability to be maintained on the market. This element is important for us because we have found previously in the price equation that suppliers reduce the price of energy inefficient appliances when electricity prices increase. Such reductions in the purchase price may therefore allow them to maintain inefficient products on the market when electricity prices go up.

Table 1.4: Fixed effect dynamic probit estimation of product offer based on Wooldridge (2005)

Dependent variables	Eq. (9): Log market share of product *j* Eq. (10): Price of product *j*
The product was commercialised the year before (k_d)	0.9225*** (37.14)
Imputed appliance price (k_p)	-0.0016*** (-13.09)
Expected and discounted running costs (k_c)	-0.0032*** (-5.05)
The product was commercialised in 2002 (k_1)	-0.6057*** (-17.53)
Nonredundant explanatory variables covering all time periods and including time-constant product features (k_z)	Yes
Year dummies	Yes
Observations	12,340
Number of imputations for appliance prices	10

Notes. *t*-statistics in brackets. Standard errors are robust to heteroskedasticity, clustered on products, and take into account uncertainty regarding the imputed values of appliance prices. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

As explained previously, the dynamic fixed effect probit model of Table 1.5 has been run on imputed prices since purchase prices can only be observed when products are actually commercialized. The imputation method, and therefore the accuracy of the results of the probit model, relies on a transformation of observed prices which distribution must be normal. The transformation that we use is such that $n_0 = 0.1$ and $n_1 = 0.97$ in equation (1.11). These parameters have been chosen so that $\tilde{p}_{j,t}$ is approximately normally distributed. Furthermore, we perform the Skewness and Kurtosis test on $\tilde{p}_{j,t}$. The p-values of this test is 0.30. It therefore does not reject the hypothesis of normality of $\tilde{p}_{jt}$.

6. A simulation of electricity price increase

If further reductions in energy consumption are a policy objective for domestic appliances – and there are many reasons to believe that it should be so[20] – the above results allows to quantify the impact of an increase in electricity prices on energy use taking into account both consumer and producer responses. In this section, we simulate the effect of a 10% increase in the price of electricity. Recall that the above results describe three adjustments, which can be viewed as occurring in different time horizons. In the short term, consumers

[20] One reason is that, for 2020, the European Union has a target of 20% savings in its primary energy consumption compared to projections. Energy efficiency is one of the means to achieve this objective. In 2011, the European Commission estimated that the EU was on its course to achieve only half of his objective (European Commission, 2011a).

adjust their purchase behavior. In the mid-term, manufacturers and/or retailers modify prices and they revise their product offer in the long-term. Likewise, our simulation builds up on these three impacts.

To assess the short run impact of an electricity price shock on market shares, we use the estimates of the sales equation to predict product *j*'s market shares s_{jt}. Based on the values obtained for each product *j* at time *t*, we calculate the market averages for the purchase price, the electricity costs, the capacity and the energy consumption (in kWh/year) of sold appliances both in a baseline scenario (with historical prices) and in a scenario with a 10% increase in the price of electricity. To evaluate the medium term impact associated with retail price adjustments, we use the purchase price equation to predict the impact of the electricity price increase on p_{jt}. We then recalculate market shares with the new prices. Finally, we introduce changes in product offer by using the results of the dynamic probit model on product availability. More precisely, we compute the predicted probabilities that each product j in our sample is put on the market without and with the 10% electricity price increase. We respectively denote these probabilities $\hat{d}_{jt}$ and $\hat{d}_{jt}^{10\%}$ and then calculate their ratio ($\hat{d}_{j,t}^{10\%}/\hat{d}_{j,t}$), which we use to weight the market shares of each product j in the scenario with a 10% electricity price increase.[21]

We need to make three additional assumptions. First, we assume that the increase in the price of electricity does not have any impact on the total amount of sold appliances.[22] This is not unrealistic since purchases of refrigerators are mostly replacements and households are unlikely to do without a refrigerator because of an increase in the price of electricity. However, increases in the price of electricity could temporarily trigger additional purchases by consumers who possess relatively energy-inefficient products and therefore want to replace them: this transitional effect is not taken into account in the simulation. Second, our specification uses the expected electricity prices, not the real price. In order to calculate the impact of the price increase, we assume that expected electricity prices would rise proportionally with real electricity prices (hence, by 10%). Third, we neglect the impact of a

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[21] In the simulation, we only use the observations for which we have predictions for market shares and prices. Furthermore, $\hat{d}_{j,t}^{10\%}$ is inclusive of the impact of the electricity price shock on both running costs and purchase price adjustments. It is however not computed in a dynamic fashion: we do not take into account the fact that $\hat{d}_{j,t}^{10\%}$ has an influence on $\hat{d}_{j,t+1}^{10\%}$, $\hat{d}_{j,t+2}^{10\%}$, etc.

[22] Our model cannot predict the evolution of the market share of the outside good under a 10% increase in the price of electricity and, therefore, it is not possible to determine how the total amount of sold appliances would evolve.

change in the size of nests on the market shares of individual products since this effect is likely to be very small.

Simulation results are displayed in Table 1.6. The variable of interest from a policy point of view is the level of energy use. The long-run elasticity of energy consumption to electricity price is rather low: minus 0.09 after accounting for both demand and supply adjustments. Consumer myopia partly explains this pattern. Recall that the attention parameter is about 0.65, meaning that a 10% increase in electricity cost corresponds to a 6.5% increase if consumers were fully rational. This explains why, in the short run, the energy consumption of sold appliances decreases by 3.2% (See column i).

But the differences between short-, medium-, and long-term elasticities also show the importance of producer behaviour. In particular, price revisions by producers almost cancel the impact on energy use: the elasticity before and after price adjustment is respectively -0.32 and -0.004. On the contrary, product innovation reduces energy consumption as the products available in the market use less energy in average after changes in product offer.

It is worth discussing more deeply the negative impact of price adjustments on energy use. It is driven by the fact that the producer response is asymmetric: energy-intensive products experience larger cuts than energy efficient products. In this way, retailers and producers compensate more the increase in discounted electricity costs for poorly efficient appliances. This is visible in Table 1.7 that displays the long run simulation results (column iii) with a breakdown by energy efficiency class. Demand shifts from energy-consuming to energy-efficient appliances to a limited extent because suppliers compensate for the higher increase of the electricity costs of less efficient products by decreasing their purchase prices more. This supply-driven "rebound effect" is made possible by the fact that the market is imperfectly competitive due to product differentiation. In a competitive market where the price equals the marginal cost of production, producers would have less latitude in their pricing strategies.

Table 1.5: Simulated impacts on average purchase price, electricity cost, and annual energy consumption of a 10% increase of the electricity price

Sales-weighted averages	Baseline	Electricity price 10% higher		
	Initial values	Short term impact on market shares (i)	Impact with purchase price adjustments (ii)	Impact with purchase price adjustments and change in product offer (iii)
Average purchase price (A)	279.4	-8.3 (-3%)	-24.2 (-8.6%)	-25.1 (-9%)
Average lifetime electricity cost (B)	375.9	21.7 (5.8%)	37.4 (10%)	33.2 (8.8%)
Average total net present costs (A+B)	655.3	13.4 (2%)	13.3 (2%)	8.1 (1.2%)
Average energy consumption (kWh/year)	326.2	-10.4 (-3.2%)	-0.1 (0.04%)	-3.1 (-0.9%)

Notes. Relative changes in brackets in second to fourth column.

Table 1.7: Simulated impacts of a 10% increase of electricity price by energy efficiency class

Energy efficiency rating	Relative change in prices	Relative change in sales
A+	-2.3%	5.78%
A	-5.3%	3.08%
B	-6.3%	0.48%
C	-8.0%	-0.70%
D	-10.4%	-1.28%
E	-12.1%	0.79%
G	-18.8%	-4.52%

Note: The relative change in sales is based on the total market share of each energy efficiency class, the relative change in prices on the average price within each energy efficiency class. For example, sales of "A+" appliances increase by 5.78% with a 10% electricity price increase, and their average price decrease by about 2.3%

The analysis thus points out that the impact of energy prices on energy use is plagued by two inefficiencies: demand-side investment inefficiencies and imperfect competition in the refrigerator market which gives room to producers to cushion the impact of power price increase with an asymmetric price response. It is then worth calculating what would be the elasticities had these inefficiencies not be present. Results are displayed in Table 1.8 which compares our results with a hypothetical scenario where consumers are perfectly rational ($\gamma = 1$) and the refrigerator market is competitive, which means no purchase price adjustment in the (realistic) case where marginal production costs are constant. The long-term elasticity would more than double (from -0.32 to -0.71). The table also shows that the inefficiency related to imperfect competition is larger than the impact of consumer myopia:

the long term elasticity -0.15 with imperfect competition and perfect rationality and -0.46 when consumers become myopic under perfect competition.

Table 1.8: Simulated impacts on average purchase price, electricity cost, and annual energy consumption of a 10% increase of the electricity price

	Electricity price 10% higher		
Relative change in average energy consumption (kWh/year) as compared to the baseline	Short term impact on market shares	With purchase price adjustments	With purchase price adjustments and change in product offer
Consumers are myopic and competition is imperfect	-3.2%	-0.04%	-0.9%
Consumers are perfectly rational but competition is imperfect	-4.9%	-0.05%	-1.5%
There is perfect competition but consumers are myopic	-3.2%	-3.2%	-4.6%
Consumers are perfectly rational and there is perfect competition	-4.9%	-4.9%	-7.1%

These simulation results convey three important policy messages. First, imperfect competition can be a bigger problem than myopic behavior for the social planner attempting to increase the energy efficiency of domestic appliances. Even if consumers would value the future cost of energy consumption correctly when they purchase appliances, taxing energy would still have an attenuated impact in markets for domestic appliances because suppliers are able to cushion the impact of electricity price shocks on the sales and obsolescence of the most energy consuming appliances.

Second, the long term impacts of electricity price shocks on product offer can be relatively important. In our case, omitting these would lead to underestimate the elasticity of energy consumption to electricity prices by about 40%. Anyway, this also implies that the two inefficiencies do not only have short run impacts on the sales of energy efficient durable goods, but also have long-lasting effects on product offer and suppliers' incentives to innovate. These long-lasting effects are important in magnitude and can be severely affected even at moderate levels of consumer myopia or imperfect competition.

Another lesson is that the two inefficiencies are partly "substitutes", in the sense than an increase of the size of one reduces the importance of the other. So, if consumers are less myopic, the producer incentives to reduce the price of inefficient models are higher, and conversely. A policy implication is that energy labelling, which only addresses the first inefficiency, may exacerbate the second problem. In contrast, other policy options – energy performance standards, feebates, subsidies for efficient models, eventually combined with taxes on inefficient models – do address both problems.

7. Conclusion

The existing literature suggests that consumers' implicit discount rates for cold appliances are suspiciously high, implying that consumers would be myopic and would not take future energy costs into consideration when purchasing refrigerators. By using a discrete choice model applied to UK market-level panel data to estimate consumers' valuation of energy savings, we find that consumers undervalue future energy costs by 35%, which is equivalent to applying an implicit discount rate of 8.7% to the stream of future electricity costs when calculating the net present value. Such a finding substantially moderates our perception of the importance of consumer myopic behavior as a barrier to energy efficiency investments. This result is robust to many factors, in particular the average lifetime of appliances, expected energy prices and sampling choices. Contrary to previous investigations of appliances, our model controls for unobserved product characteristics with product-specific fixed effects and we directly estimate the weight given to energy costs by approximating rational energy price expectations with an ARIMA model. Evidence that the energy efficiency gap could be much lower than previously thought has been found with similar methodologies applied to the US automobile market (Sallee, West and Fan, 2011; Allcott and Wozny, 2012).

From a policy perspective this result suggests that the EU energy label policy, which provides consumers with information on the energy performance of appliances, has been able to mitigate investment inefficiencies. The fact that consumers finally dot underestimate too much future electricity costs could also plead for energy taxation if further energy savings is sought. However, our simulations stress the importance of another market failure which erodes the effectiveness of the energy price-based approach: as competition in the refrigerators market is imperfect, manufacturers and retailers are able to partly absorb electricity price shocks, by cutting the purchase price of the least energy-efficient appliances more.

Chapter 2: Impacts and Monitoring of the EU Policy on the Energy Labelling of Domestic Appliances

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Abstract

This chapter has been written in 2011 in the framework of a study conducted by BIO Intelligence Service for the French Agency of Environment and Energy Management (ADEME) on the *ex post* evaluation of the implementation of the EU Energy Label in France, entitled "*Bilan de l'évolution du parc électroménager français et évaluation* bottom-up *des économies d'énergie depuis la labellisation énergétique des appareils*". This chapter was originally a section in a larger report, which establishes the level of energy consumption of French domestic appliances and assesses the energy savings imputable to the energy label. Updates have been made since then, mostly to include some of the results of the FP7 research project ATLETE II, in which BIO Intelligence Service indirectly participated as a service provider for the ADEME.

This chapter presents the EU policy of an energy label along with its principal effects and identifies two conditions that are necessary for the policy to be effective in reducing the energy consumption of domestic appliances: the visibility of the label and the accuracy of the information that is supplied to consumers. Whereas the notoriety of the energy label has largely widened during its 18 years of implementation, the controls on the correctness of the information that is displayed still remain insufficient. This chapter therefore encourages French and EU public authorities to guarantee more frequent checks to ensure that the energy savings that are promised correspond to the real energy savings of the energy-efficient products that are on the market.

Résumé du chapitre 2 en français

Ce chapitre a été rédigé en 2011 dans le cadre d'une étude menée par BIO Intelligence Service pour le compte de l'ADEME sur l'évaluation ex-post du dispositif d'étiquette énergie en France, intitulé *Bilan de l'évolution du parc électroménager français et évaluation* bottom-up *des économies d'énergie depuis la labellisation énergétique des appareils*. Il s'agit d'une section au sein d'un rapport plus important, qui établit par ailleurs le niveau de consommation du parc électroménager français et tente d'évaluer les économies d'énergie imputables au dispositif d'étiquette énergie. Des mises à jour ont été apportées depuis à ce chapitre principalement pour y inclure certains des résultats du projet de recherche ATLETE II, auquel a indirectement participé BIO Intelligence Service en tant que prestataire pour l'ADEME.

Ce chapitre présente le dispositif d'étiquette énergie, ses principaux effets avant d'identifier deux conditions nécessaires pour que le dispositif soit efficace pour réduire la consommation énergétique des appareils électroménagers : sa visibilité auprès des consommateurs et l'exactitude des informations fournies. Tandis que la notoriété de l'étiquette énergie s'est largement accrue au cours de ses 18 années de mise en œuvre, les contrôles sur l'exactitude des informations fournies demeurent encore insuffisants. Ce chapitre encourage donc les pouvoirs publics français et européens à garantir des contrôles plus fréquents pour que les économies d'énergie affichées correspondent aux économies réelles des appareils commercialisés.

1. General presentation of the EU Energy Label

Since 1995, the reactivity of households to energy issues has been stimulated by an EU-wide information-based measure: the energy labelling of domestic appliances. EU Directive 92/75/CEE defines the implementing modalities of an energy label for domestic appliances. Following this Framework Directive, specific regulations have been adopted for each category of products, such as Directives 94/2/CE, and then 2003/66/CE for refrigerators, freezers and their combinations; Directives 95/12/CE and then 96/89/CE for washing-machines; or Directives 97/17/CE, and then 1999/9/CE for dishwashers.

The labelling system steadily gained popularity among European consumers. This has been observed in France thanks to various surveys conducted by TNS/Sofres. In 1997, two years after the enforcement of the EU Energy label, only 20% of the French consumers declared that they knew the EU Energy Label. It has however progressively gained ground and it is today known by the majority of consumers: 67% of French consumers declared that they knew the label in 2003, and 84% in 2009.

The diffusion of energy efficient products at lower prices has spurred the EU to introduce two new energy efficiency ratings for cold appliances in 2003: “A+” and “A++”. These two new categories have been added above category “A” to provide the market with products that are even more energy efficient and to encourage manufacturers to develop even more efficient products.

Furthermore, a revision of the EU energy label in 2010 has clarified the content and the scope of the new system of energy efficiency categories, with the creation of the “A+++” rating. The new version of the EU Energy Label has been defined in Directive 2010/30/UE. Figure 2.1 displays the two versions of the EU Energy Label for a combined refrigerator-freezer: the old one and the new one currently enforced.

In comparison with the old version, the new EU energy label has been modified in the following ways:

- It includes up to three more energy efficiency categories (i.e. categories “A+”, “A++” and “A+++”) with respect to the old A to G classification;
- It is identical in all the Member States;

- It is linguistically almost neutral, as the great majority of the texts have been replaced with pictograms;
- It is printed on a unique document; and
- It displays the noise level of products in a much more visible manner.

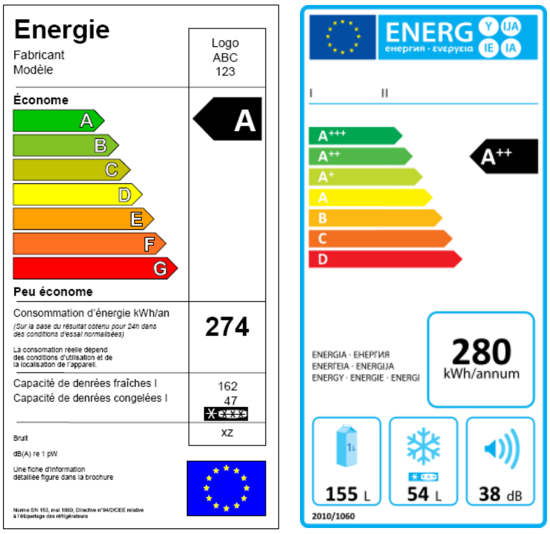

Figure 2.1 : Old and new energy labels (example for a combined refrigerator-freezer) (Mudgal *et al.*, 2011)

2. Expected effects of an energy label

Domestic appliances that are similar in terms of technical and usage characteristics can differ substantially in terms of energy efficiency. If there were no energy label on electric appliances, most consumers would very likely purchase (without knowing it) the most energy inefficient goods. This is because the most energy efficient appliances are also the ones that are most expensive to produce. The price signal at the time of purchase would therefore encourage consumers to buy the least expensive goods without accounting for their operating costs. In the end, purchasing decisions would be biased in favour of inefficient products.

Not only would this create an information failure so that energy inefficient goods are purchased in the short run, but it would also have a long-run effect on the types of products available on the market. As soon as consumers would systematically purchase energy inefficient goods, manufacturers would no longer have any incentives to commercialize energy efficient appliances. The lack of interest for energy efficient appliances would therefore not encourage manufacturers to innovate in the long run.

The main purpose of an energy label is therefore to tackle a market failure of imperfect information, by making a hidden dimension of the quality of an energy-using product visible, i.e. providing information about energy efficiency and the cost of usage of goods. As soon as an energy label allows distinguishing the energy inefficient goods from the energy efficient ones, consumers are able to choose the appliances which are best for them according to their own preferences: some may continue to purchase energy using products by choice or due to immediate financial constraints, but others may well decide to purchase energy efficient products. By providing consumers with a very relevant piece of information, they can make rational choices which, at a larger scale, contribute to rationalize domestic energy use.

The impact of the energy label on the sales of energy efficient products is the most direct impact that can be associated to this policy. However, it is likely that the energy label has medium to long run impacts on consumer preferences (by increasing their awareness of energy and environmental issues) and on the offer of energy efficient products. The most likely impacts of the energy label are described below.

Impact on sales and prices

The energy label reduces information search costs that may lead to energy inefficient goods being favoured by consumers. It allows correcting the market tendency to favour energy inefficient goods. Therefore, the most direct impact of the energy label on the appliance market should be an increase of the average energy efficiency of sold appliances.

However, an impact on prices is also very likely. It is probable that the increase in the demand for energy efficiency alters the structure of market prices: because the energy label makes energy efficient appliances more attractive, it is likely that this policy increases the price of energy efficient appliances relatively to the price of energy inefficient appliances. Therefore, a shift in demand in favour of energy efficient appliances may well lead to an increase in both the sales level and the price of energy efficient appliances with respect to their energy inefficient counterparts.

Impact on consumer behaviour

In the medium run, the energy label also makes consumers more aware of the problem of energy misuse. Generally speaking, it may contribute to a change in consumer mentality with respect to their use of energy: by giving a new visibility to the matter of energy efficiency, the energy label may change, in the medium run, consumers' preferences for energy efficient products (on the domestic appliance market and on any other market for energy-using products) and also change their behaviour as users of these products. These shifts of consumer preferences and habits could well be additional benefits of the energy label, which may educate while it informs.

Unfortunately, determining the impact of the energy label on consumer awareness and on their behaviour as users of domestic appliances is difficult. Above all, this would require a better understanding of the determinants of the intensity of use of domestic appliances. In this respect, the educative feature of the energy label let us hope some positive effect of the energy label on rationalizing consumers' utilization of domestic appliances. However, the decrease in the marginal cost of use associated with higher energy efficiency could generate *rebound effects*, i.e. more intensive and less caring uses of domestic appliances. The question is then to know if the introduction of more efficient appliances can lead to a significant decrease of domestic energy consumption, or if any increase in energy efficiency is offset by a parallel increase of the intensity of use of appliances. Greening *et al.* (2000) have reviewed 75 studies which aim to estimate the rebound effect of energy-using products. Depending on the type of product, the rebound effect could vary between 5% and 40% of the initially forecasted energy savings. This means that 5% to 40% of the savings expected from the purchase of more energy efficient appliances may be compensated by increases in the frequency of use of the appliances.

Very few studies have tried to analyse the rebound effect of washing-machines and dishwashers, which are the white goods which frequency of use can vary the most (contrary to cold appliances). Woersdorfer (2010) explains that the automation of clothes-washing and the massive diffusion of washing machines in households since the 50s explain the sharp increase in the quantities of clothes washed per household (525kg in 2000 vs. 277kg in 1960 in Germany). This author notes that, by the 1990s, the need for washing became satiated. Therefore, we could expect today that the diffusion of more energy efficient washing machines thanks to the energy label would not lead to a massive increase in the frequency of utilization in the future. In this respect, Davis (2008) implemented a field experiment in which old washing machines were replaced freely by new, energy efficient ones in the sample of households that were part of the experiment. Whereas the energy savings associated with replacing the old appliances were about 40%, the increase in the frequency of use was only around 5.6%. The rebound effect would therefore be relatively modest for this category of product according to the results of Davis (2008).

Impact on manufacturers' incentives to innovate

In parallel to a shift in the demand for electric products, the energy label may structurally alter supply on the domestic appliances market. By encouraging consumers to prefer energy efficient products, the energy label gives manufacturers some incentives to outperform other manufacturers by offering innovative, energy-efficient appliances. The energy label, as it puts products into competition according to their energy efficiency, fosters research and the development of new products. This effect may well offset the tendency of the energy label to make more energy efficient products also more expensive, because innovation may, in the medium term, reduce the production cost of energy efficient products.

3. The determinants of success

The positive impacts that can be attributed to an energy label however depend on various factors. In particular, the attribution of an energy label to any product on the market requires the involvement of suppliers and dealers, which must put on each appliance an energy label in conformity with regulation. The success of the policy essentially depends on the commitment of these two actors.

The role of suppliers

Suppliers[23] must establish the technical documentation that is necessary to produce the energy label, and must provide freely the energy label that dealers will put on their products. Suppliers are responsible for the accuracy of the information that they provide, and must make the technical documentation available to the inspectors that assess the accuracy of the information on the label.

The quality of the information provided on the energy label therefore depends on the quality of the work of suppliers to be in compliance with regulation. To avoid frauds, EU Member States must guarantee that suppliers fulfil their obligations. In practice, gaps between real energy consumptions and the ones mentioned on the energy labels exist.

[23] The word "supplier" is defined in Directive 2010/30/UE as "the manufacturer or its authorised representative in the Union or the importer who places or puts into service the product on the Union market".

During the first years of the implementation of the EU energy label, Winward, Schiellerup and Boardman (1998) have estimated that less than 50% of the products commercialized in the EU would have had an energy label that matched the real energy efficiency level of products. The other half was over-rated. One reason is that the methods used to measure energy consumption may vary. An additional uncertainty remains: manufacturers have the right to a technical margin of error, which makes over-rated appliances compliant in the limits of this level of tolerance. Consumers are of course not able to check for over-rating due to the technical margin of error at the moment of purchase. Only independent organisms or competitors can expertise products, which is costly.

In some cases, as the Swedish Energy Agency (2006) mentions for Sweden, the appliances that are inspected are no longer produced by the manufacturer, and in some cases, the latter does not keep the relevant technical information during the legal duration of five years after the date of manufacturing of the last appliance. The verification of the accuracy of the information on the energy label can also become very difficult when a supplier gives the same name to a new version (that has different technical characteristics) of a product which is no longer manufactured.

More recently, the research project ATLETE[24] has tested the accuracy of the energy label displayed on 80 refrigerators. The check included all the criteria presented on the label and not only the energy category of the appliance. According to the results of ATLETE, 79% of the products were correctly labelled in terms of energy efficiency rating. A wave of similar tests is currently ongoing for washing machines in the framework of ATLETE II (2012-2014), the follow-up of ATLETE. Besides, a questionnaire geared to Member States in the framework of ATLETE II, and elaborated by BIO Intelligence Service, brings a few pieces of information regarding the accuracy of the energy label to display the actual energy consumption of appliances. In particular, Denmark has performed 500 tests on energy-using products in 2011 and found an accuracy rate of 80%. Still a non-negligible minority of products would be over-rated.

This explains why some suppliers are worried about the distrustful practices of competitors that display labels that are likely to be very optimistic regarding the energy consumption of their appliances (Winward, Schiellerup and Boardman, 1998; Swedish Energy Agency, 2006).

[24] ATLETE project: Appliance Testing for Energy Label Evaluation. http://www.atlete.eu/. Website last consulted in January 2014.

Because producing appliances that are energy inefficient is less expensive, for a same type of appliances, the unfair competition of over-rated products may affect the market shares of the products that are correctly rated. Thus, even a small proportion of over-rated appliances can be a threat for the energy label: it is enough if consumers believe that the difference in prices within a same energy category is due to a difference in competitiveness, and not to a difference in energy efficiency or product quality. For the moment, and as explained on the ATLETE I and II reports on Member State activities, France is among the half of the Member States that has not enforced any control policy regarding the accuracy of the energy label as compared with the real energy performance of products.

Beyond the need to reinforce controls on the energy efficiency of products, it is essential that the energy label encourages the purchase of products which environmental footprint, as much as their energy consumption, is lower with respect to other products. It is therefore essential that product-level energy efficiency policies are understood as one part of the more general need for ecological and socially responsible manufacturing. In this context, surveillance activities are not the only ones that may be foreseen. Strengthening manufacturers' commitments in terms of good environmental practices could also result very fruitful.

The role of dealers

Whereas the energy labels must be provided freely by suppliers to dealers, dealers are responsible for displaying the energy labels in retail shops, on each appliance and on a very visible place. In practice, the energy label is not always put in a visible part of the appliance, the legal format of the label is not respected, or the label is sometimes simply missing. The Swedish Energy Agency (2006) finds three main reasons that explain that sometimes the energy label is not properly displayed:

- The lack of time and neglect of some. Furthermore, frequent new arrivals of products explain that the energy label is not always put on the products on time.
- Products in aluminium and steel have sometimes been stained by the glue used to stick the energy label. For these products, some dealers are no longer putting the labels in a visible place outside the products, but on the inside. The responsibility of suppliers is then involved, because they must provide glue that is adapted to the products that they sell.

- Some labels are printed in black and white, to make savings or when dealers are waiting for coloured labels from their suppliers. This is not compliant with current regulation and makes the energy label not as visible as a coloured label.

In France, the *Direction de la Concurrence, de la Consommation et de la Répression des Fraudes* (DGCCRF) is in charge of controlling whether the energy label is present or not on the appliances for which it is compulsory. In the EU, a campaign in 149 retail shops occurred in 1997 and showed that most of the domestic appliances were not correctly labelled soon after the implementation of the old policy on energy labelling: only 44% of the 7,104 products that were inspected (51% of the inspected products in France) had their energy label conform with regulation (Winward, Schiellerup and Boardman, 1998). In 2010, the majority of the appliances appeared to be correctly labelled. According to project ATLETE (2009-2011), the percentage of products correctly labelled was between 71% and 80% in French retail shops. In most cases, non-compliance was due to the use of a black and white label instead of a coloured one. This may look anodyne, but the coloured display makes the energy label much more visible in a retail shop than a black and white display. Therefore, the black and white display reduces the impact of the energy label on the decisions to purchase energy efficient appliances.

Besides, the questionnaire realized by BIO Intelligence Service for the ADEME and addressed to Member States in the framework of ATLETE II allowed identifying, for some Member States, the number of inspected shops and the percentage of correctly labelled products. The results of the questionnaire are presented on Figure 2.2 and Figure 2.3. There is some high heterogeneity in the amounts of tests performed by Member States. Furthermore, the degree of compliance with regulation ranges from 40% for Cyprus to more than 90% in other EU countries.

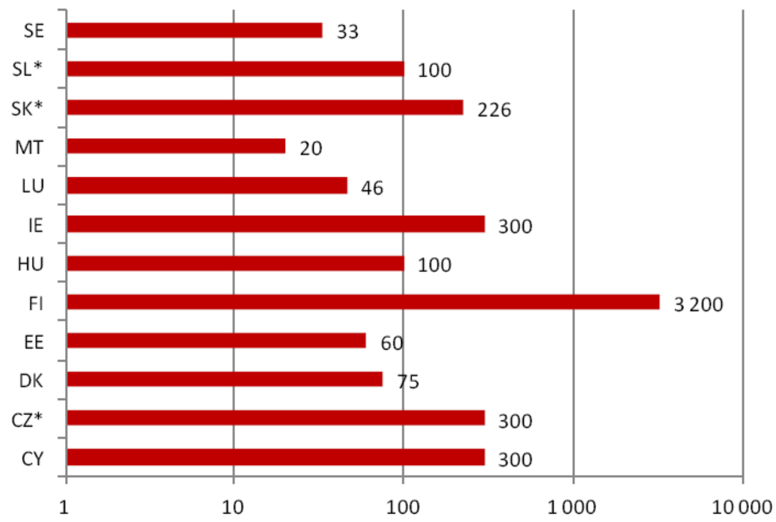

Figure 2.2 : Amount of shops inspected every year in a selection of Member States (Pahal *et al.*, 2013)[25]

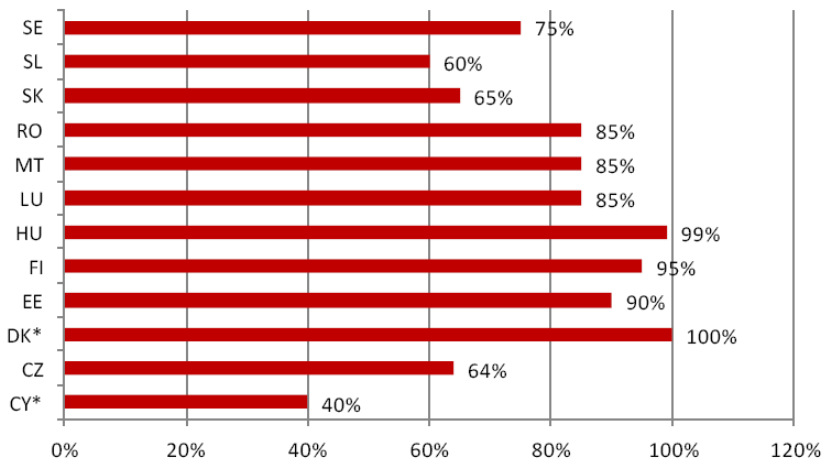

Figure 2.3 : Percentage of products complying with EU regulation on the display of the energy label on domestic appliances in a selection of Member States (Pahal *et al.*, 2013)[26]

Synthesis of expected impacts

Figure 2.4 sums up the main impacts expected from the implementation of an energy label. The positive impacts are displayed in green whereas the negative ones are in red.

[25] *: CZ checked 4 shops in 2010, 18 in 2011, and 300 in 2012. SK checked 226 in 2011, no data for 2012. SL checked approximately 100 shops per year in 2009 and 2010

[26] In DK, compliance eventually reaches 100%. Sometimes three visits are necessary but compliance is reached. After the third visit the case, in the advent of non-compliance, the case goes to court. In CY, the level of compliance has been 40% after the first inspection. However, similarly to DK, further inspections are carried to the non-compliant shop in order to increase the level of compliance.

This research highlights that an energy label can be threatened by risks which can lead to market distortions in the worst cases. If the energy label is not visible in shops, consumers will never know about it. At the same time, the display of a favourable energy label constitutes a commercial advantage for manufacturers. It is essential that the accuracy of the displayed information is controlled else dishonest suppliers could appropriate the benefits of such an advantage without keeping their promise of higher energy efficiency. This type of frauds could have heavy consequences for the labelling policy, in the short run as energy inefficient goods could be unduly sold, but also in the long run on the notoriety of the energy label among consumers, suppliers and dealers.

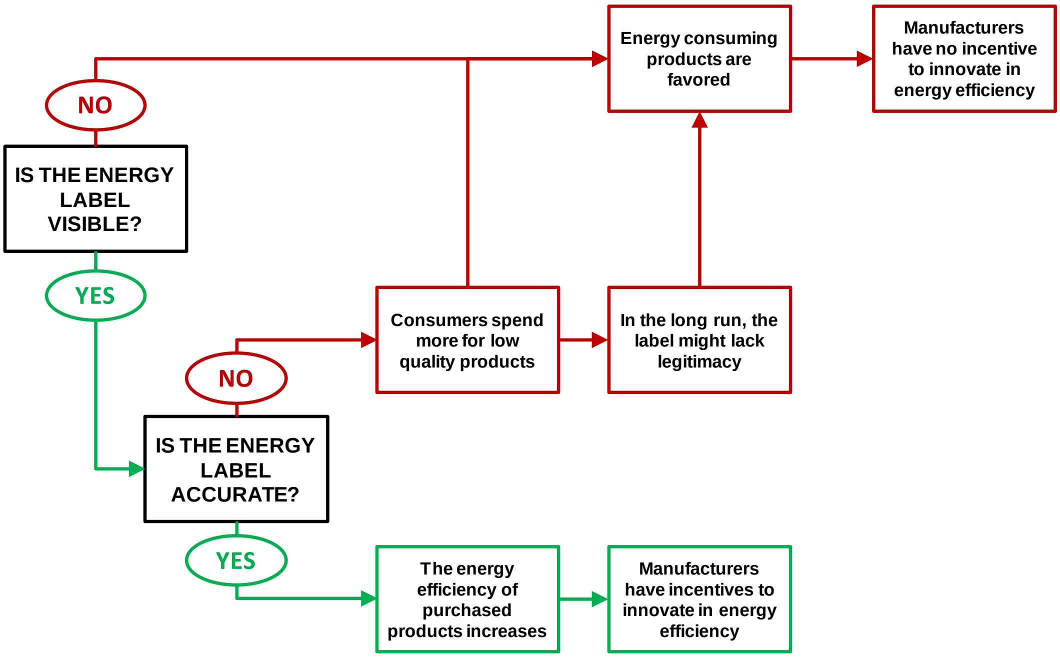

Figure 2.4 : Diagram of the positive and negative impacts of an energy label, depending on its enforcement (based on Mudgal et al., 2011)

4. Maximizing the effectiveness of the energy label

The energy label is a policy which seems to have had a positive impact, and sometimes even a very positive impact, on consumers' purchasing decisions towards energy efficient appliances. However, its key implementation factors need to be strengthened. With this objective, four levers of action could be promising:

- ***Increasing awareness among consumers at the same time***: it is very likely that the energy label makes consumers a bit more aware of the need to save energy while it informs them. However, its main objective is to provide information to consumers, who are free to purchase or not to purchase energy efficient products. Therefore, one of the main drivers of the impact of the energy label on purchasing decisions is that consumers are perceptive about energy and environmental matters. The potential of the energy label as an information policy for consumer is only fully exploited if consumers are, at the same time as the energy label is enforced, attentive to energy and environmental issues.

- ***A perfect match between displayed and real energy savings****:* when the energy label does not correspond to the real energy performance of a product, so that displayed and real energy consumptions do not match, consumers may pay for a low quality product at a high price. A wrong indication on the energy efficiency of a product is therefore worse than any indication at all. Furthermore, a false display leads to energy consumptions that could have been avoided, because consumers were ready to invest in energy efficient appliances.

- ***Good visibility in retail shops***: this is obvious, but good visibility is the *sine qua non* condition for the energy label to influence decision-making. If the energy label is not properly displayed (e.g. display in black and white or inappropriate place for the display), many consumers will not pay attention to it.

- ***Competitive and proactive markets***: by highlighting the interest of energy efficient products, the energy label can increase the selling price of these appliances. This increase in prices caused by the energy label can slightly reduce the effect of the latter on energy savings. With current information, it is difficult to know to what extent the energy label might have or might not have had an impact on the selling price of energy efficient products. However, this effect on prices is likely to be small under high competition. At the same time, the energy label plays a role in the long run on innovation. This effect requires that manufacturers have an incentive to make better products than their competitors: in this matter as well, healthy competition between manufacturers is required for the effect on innovation to be significant.

Maximum effectiveness requires that all these four drivers are properly accounted for. Consequently, they constitute operational objectives of proper enforcement of the EU energy label. We therefore encourage policy makers to monitor the energy label throughout these four dimensions year after year.

Additionally, a fifth element should be considered when assessing the capacity of the energy label to generate environmental benefits. In fact, the energy label is effective as soon as it favours the purchase of energy efficient products. However, the assessment of the environmental benefits associated with the policy may not be limited to the average energy performance of products, but could take into account more general elements, such as the evolution of the energy consumption of the entire stock of running appliances (which depends on energy efficiency, but also on average product size and frequency of use) and the environmental impacts of products throughout their lifecycle. It may be necessary to look at the question of the energy efficiency of appliances within the framework of the more general questions of eco-design, manufacturing and sustainable consumption. In this matter, encouraging industry to adopt principles of eco-design and corporate social responsibility is important. In the case of domestic appliances, this could directly reflect on the environmental impact of manufactured goods throughout their lifecycle, including the design of compact goods appropriate for all types of households, so as to avoid that the energy consumption of products increases due to the increase of the average size of products.

Figure 2.5 structures the objectives associated with the implementation of the energy label. It integrates this last dimension among the operational objectives connected to the good implementation of the policy.

For each operational objective except the one related to corporate social responsibility, monitoring indicators are suggested in Appendix B. For each indicator, a factsheet describes the content of the indicator, how to measure it, use it and also its interest for the monitoring of the energy label. Ideally, at least one monitoring indicator for each objective should be scrutinized.

These indicators have been chosen so that they could be easily collected by public authorities, in particular using consumer surveys. This is why these indicators are above all based on declarations from consumers, and not on observed data. We are aware of the limits of using declarations, in particular of the risk of hypothetical bias that could affect the outcomes. However, with the sole objective of monitoring the energy label, values in levels are as relevant as their year-on-year evolution. In this context, and as soon as there is no reason to think that the magnitude of declarative biases would change from one year to the other, monitoring indicators collected with surveys can perfectly match the needs of public authorities, i.e. to have information on whether the implementation of the energy label is more effective today than in the previous years to reduce the energy bill of households.

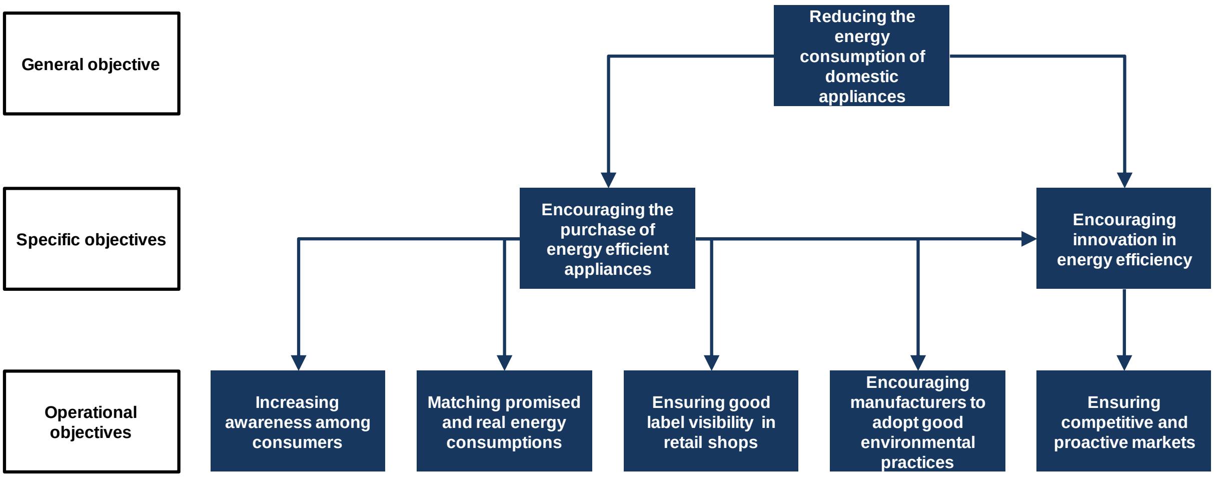

Figure 2.5 : Diagram of objectives associated to the energy labelling of domestic appliances[27] (based on Mudgal *et al.*, 2011)

The list of indicators is displayed below, whereas their more detailed analysis has been put in Appendix B:

- On Increasing awareness among consumers: 1) the percentage of consumers that declare that energy efficiency matters in their purchasing decisions; and 2) the amounts of money consumers would be willing to pay to increase the energy efficiency of the products that they purchase.
- On matching displayed and real energy savings: 3) the percentage of products that have been checked and for which the rating on the energy label corresponded to the real energy consumption of the appliance.
- On in-shop visibility: 4) the percentage of controlled products in shops and on the Internet complying with the regulation on the display of the energy label.
- On competition between brands producing domestic appliances: 5) the Herfindahl-Hirschman index on market concentration; and 6) the mean and the maximum energy efficiency rating of the most energy efficient appliance sold by each supplier.

[27] The objectives mentioned in this paper correspond to the enforcement of the EU label and do not include all the issues before implementation regarding the design of the energy label (e.g. how to make it easy to understand, attractive to consumers, etc.).

5. Conclusion

Since its enforcement, the EU energy label has acquired an increasing popularity among consumers. It has furthermore been reshaped to become easier to implement for suppliers and dealers in all the EU Member States, in particular thanks to the replacement of texts by pictograms, and to take into account technical progress in energy efficiency, with the creation of the energy efficiency categories “A+”, “A++” and “A+++”.

This research shows that the effectiveness of the energy label relies on two fundamental elements: a good visibility and the accuracy of promised savings with the energy consumption of appliances. Whereas compliance with the regulation is relatively high among dealers and suppliers, both in terms of a correct display and of a proper match between promised and real energy consumptions, margins of improvement remain, in particular through a strengthening of market surveillance activities.

Moreover, the accuracy of displayed consumptions appears to be priority as compared with the issue of in-shop visibility, because even a minority of non-compliant products on the matter of accuracy of displayed consumptions can seriously damage the policy. Not only can consumers be cheated on, but this risk is high for those who would like to purchase the least expensive products within an energy efficiency category. In fact, these least expensive products within an energy efficiency category might well correspond to the ones for which the risk of fraud is higher, considering that fraudulent products are less costly to produce. Besides, all the legitimacy of the label relies on a good match between promised savings and real energy consumptions. In the long run, insufficient action to ensure a perfect match between displayed and real consumption levels could bring the energy label into disrepute.

PART II. The Impacts of Climate Change on Energy Investment Behaviour

Chapter 3: Decision-Making in the Electricity Sector under Climate Uncertainty: a Literature Review

François Cohen, Claire Barnett, Nial Lawlor and Lorcan Lyons

The authors thank Directorate C, "Mainstreaming adaptation and low carbon technology", *of the Directorate-General for Climate Action of the European Commission (DG CLIMA) which has planned this research.*

Abstract

This chapter has been written in 2013 in the framework of a study conducted by AMEC, BIO Intelligence Service and Milieu for the Directorate-General for Climate Action (DG CLIMA) on framing investment decisions in the energy sector to adapt to climate change. The results of this project were gathered in a report entitled *Decision Making under Uncertainty in the Context of Future Climate Change: Applications in the Energy Sector*. This chapter was originally the first part of this report, which additionally includes two case-studies of investment decisions potentially affected by climate change. The first case study is derived from the experience of a UK company, the National Grid Electricity Transmission, whereas the second relates to the installation of a smart grid system at Castellón, Spain, by Iberdrola.

This chapter includes a brief description of the EU electricity sector. It then describes impacts of climate change relevant to the sector and the levels of uncertainty in projected changes, general information about the drivers of investments in the electricity sector and, finally, decision-making methods under uncertainty applicable to the electricity sector.

Résumé du chapitre 3 en français

Ce chapitre a été rédigé en 2013 dans le cadre d'une étude conduite par AMEC, BIO Intelligence Service et Milieu pour la Direction Générale Action pour le Climat (DG CLIMA) sur la prise en compte du changement climatique dans les décisions d'investissement du secteur de l'énergie. Les résultats de ce projet ont été rassemblés dans un rapport intitulé *Decision Making under Uncertainty in the Context of Future Climate Change: Applications in the Energy Sector*. Initialement, ce chapitre était la première partie de ce rapport, qui comprend par ailleurs deux études de cas de décisions d'investissements potentiellement affectés par le changement climatique. La première étude de cas est dérivée de l'expérience d'une entreprise britannique, la *National Grid Electricity Transmission*, tandis que la seconde porte sur l'installation d'un système de réseau intelligent par Iberdrola à Castellón, en Espagne.

Ce chapitre comprend une description brève du secteur électrique européen. It décrit ensuite les impacts du changement climatique qui sont pertinents pour le secteur et les niveaux d'incertitude des changements escomptés. Il comporte ensuite des informations générales sur les déterminants des décisions d'investissement dans le secteur de l'énergie puis décrit finalement les méthodes de prise de décision dans l'incertain adaptées à ce secteur d'activité.

1. Introduction

The EU strategy on adaptation to climate change was adopted on 16 April 2013 and set out aims to promote action by Member States, enable better informed decision making and promote adaptation in key vulnerable sectors. The majority of the Member State's current adaptation plans and strategies recognise the energy sector as a priority sector for action. There is however relatively little information available on the decision making tools used within the sector and whether climate change is being taken into account within them.

The original study conducted for DG CLIMA examines the decision making methods which are in current or potential use while focusing on the electricity sector. It proposes a decision making framework which sets out the steps for including climate change uncertainty in existing decision making processes. The first section of this report is the literature review below.

If the EU's targets for decarbonisation of the energy sector are to be met, there is a need for significant levels of investment. Investors in the energy sector are used to considering a range of uncertainties such as demand levels, plant availability and long term and short term costs as well as understanding the associated risks. However, where investment decisions are taken without due regard to climate change, there is a possibility that the future energy security of the EU may be at risk as temperature, rainfall and sea levels change and consequently affect the overall resilience of the sector. The risk of making inappropriate investments is correspondingly large as a result.

Electricity companies have long experience of managing uncertainty as matching electricity generated to demand is at the core of an effective and reliable industry where storage is prohibitively expensive. This includes understanding the ways in which weather influences demand and the vulnerability of assets to different types of weather. The sector therefore might be expected to have a good level of awareness of the issue of climate change.

Decision making tools used for investment analysis have already been applied to address issues in the sector arising from climate change. Examples include the discounted cash flow models and cost benefit analysis. There are also examples of broader climate risk assessments and adaptation plans developed within the sector at Member State level. There are further, more complex approaches to decision making under uncertainty which have been applied in academic studies of the sector. However, the industry is highly regulated and the fundamental requirement for firms within it is to develop a business case to support an investment decision which will meet the requirements of the regulatory body within the relevant Member State.

The literature review below provides a broad understanding of the drivers of any investment decision in the electricity sector, and analyses to what extent climate change should be considered in future investments decisions. It is structured as follows:

- General characteristics of the electricity sector in the EU (covering electricity generation, transmission and distribution) as this provides the background context;
- Climate change and the electricity sector, describing impacts of climate change relevant to the sector and the levels of uncertainty in projected changes;
- General information about the drivers of investments in the electricity sector; and
- Decision-making methods under uncertainty applicable to the electricity sector, whether they are currently in use or could be applied.

2. The electricity sector in the EU

Approximately a fifth of all the energy consumed in the EU is consumed as electricity. Even though the EU is relatively self-sufficient in terms of electric generation capacity, there is a dependency on non-EU countries for the import of fuels. Not all electricity generated by a Member State remains within it. There is a significant cross-border transport of electricity and increasing levels of coordination between neighbouring networks.

In 1996, the EU agreed to liberalise the electricity sector and this has resulted in an industry structure that reflects the aims of the implementing policy to:

- "distinguish clearly between competitive parts of the industry (e.g. supply to customers) and non-competitive parts (e.g. operation of the networks);
- oblige the operators of the non-competitive parts of the industry (e.g. the networks and other infrastructure) to allow third parties to have access to the infrastructure;
- free up the supply side of the market (e.g. remove barriers preventing alternative suppliers from importing or producing energy);

- remove gradually any restrictions on customers from changing their supplier;
- introduce independent regulators to monitor the sector."[28]

The sector is now regulated and has a degree of competition, for instance with customers able to move between suppliers. The role of the regulator is to monitor and control the sector, protecting and advancing the interests of consumers while maintaining security of supply. As a regulated sector, significant components of investment require a supporting business plan approved by the regulator in the relevant Member State.

Electricity cannot be stored cost-effectively on a large scale and utility companies therefore must aim to work collectively so that the amount of electricity generated and distributed instantaneously on the network balances the demand from customers. As stated on the EC website "Suppliers who use the networks are obliged to input the same amount of electricity as their customers take out and are charged by the network operator for any imbalances. The network operator also maintains some generating reserves with which to ensure that the network can remain in balance".[29] This leads to a need for complex relationships coordinating the elements of the electricity supply chain across a wide set of different systems from generation to customer.

Electricity generation in the EU

The majority of electricity generated by the EU-27 uses the fossil fuel sources of coal, oil and gas. The other main sources are nuclear energy (27.1%), hydropower (11.7%) and wind energy (6.4%) (data for 2011 taken from Eurostat). Total net generation of electricity within the EU-27 in 2011 was 3.11 million GWh (Eurostat), with the Member States with greatest generation of electricity being Germany (18.4%), France (17.3%) and the UK (11.3%). This is the current status of electricity generation across the sector (figures presented in 2011) but the EU is committed to reducing greenhouse gas emissions to 80-95% below 1990 levels by 2050 and this means that energy supply needs to be decarbonised (European Commission, 2010 and 2011). The European Commission (2011) sets out scenarios for transforming the current energy mix to the lower carbon sector required if GHG emissions reduction targets are to be met. According to IEA (2012), if decarbonisation targets for the energy sector in

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[28] European Commission, Competition, Energy: http://ec.europa.eu/competition/sectors/energy/overview_en.html

[29] http://ec.europa.eu/competition/sectors/energy/electricity/electricity_en.html

the EU are to be reached by 2035, 1,728 billion dollars (€ 1,290 billion) of investment in the generation of electricity will be required. Figure 3.1 shows how this investment is expected to be targeted, showing the significant investment required in renewable energy sources.

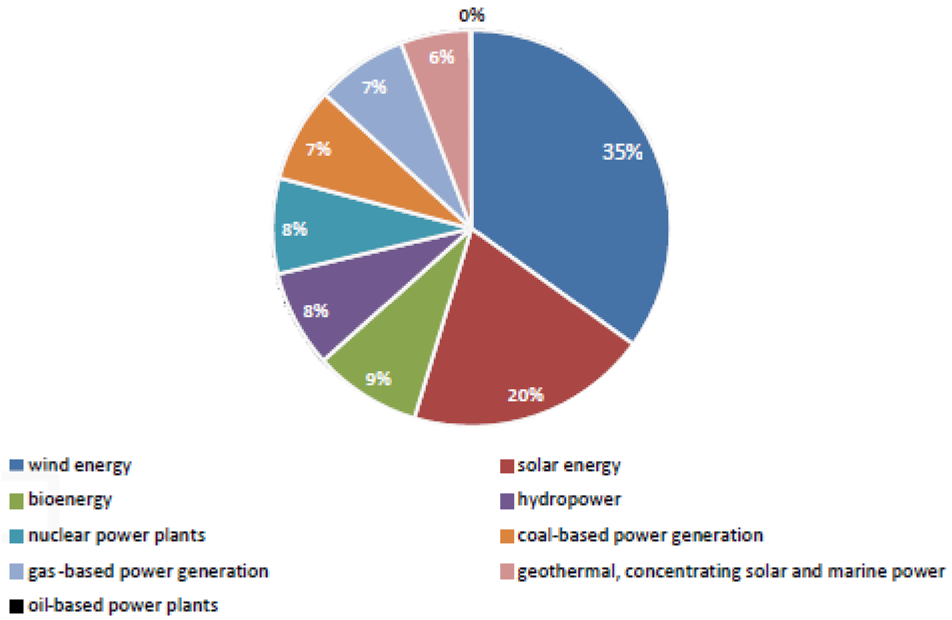

Figure 3.1: Necessary investments in electricity generation to reach decarbonisation targets by 2035 (IEA, 2012)

Except for the share of electricity that is produced by autoproducers[30] for their own needs, most of the electricity produced is purchased by intermediaries before it is resold to end consumers. As explained by Rademaekers et al. (2008), wholesale customers can purchase electricity for the purpose of resale through market exchanges, over the counter (OTC) operations or bilateral agreements. Wholesales markets include anonymous sales of electricity contracts and derivatives which help to establish a market price. There are also wholesale markets for the short- term sale of electricity (one-day ahead) for trading within the day. These are equivalent to financial spot markets. Futures contracts are also traded in anonymous wholesale markets. Futures contracts are an agreement to exchange electricity in the future (e.g. one month, one year or more) at a price agreed in the present. OTC operations and bilateral agreements are not anonymous in the first instance (though parties

[30] There are two kinds of electricity producers within the EU, those who generate electricity for sale to third parties and those who partly or wholly generate energy for their own use (termed *autoproducers*). In 2011, 8.2% of total net electricity generation in the EU-27 was from *autoproducers*. This differentiation between type of producers is relevant in terms of investment decision making as different incentives apply however, for this study, the focus is upon the wider sector so autoproducers are not considered explicitly.

may use intermediaries to achieve a measure of anonymity) and there is no central exchange as there is with spot markets.

As a result, the EU wholesale electricity power trading[31] is structured over various interconnected regional markets and is intimately related to cross-border transmission infrastructure. Wholesale market electricity prices generally move in line with the prices (over expected prices) of crude oil and natural gas (European Commission, 2012). At the same time, OTC operations are a predominant feature of electric power trading. Rademaekers *et al.* (2008) emphasise that, in 2007, the EU trade of electricity (spot and futures) would have amounted to 6.7 million GWh in 2007, which was about three times EU consumption for that year. On the other hand, total exchanges amounted to about 820,000 GWh in spot markets and 1.1 million in futures markets.

Electricity transmission

Electricity transmission is managed independently from both electricity generation and wholesale trade. In the EU, the separation of these activities is a legal obligation, as expressed in EU's third legislative package to liberalise energy markets, adopted in 2007. In particular, Directive 2009/72/EC requires the unbundling of transmission systems and transmission system operators (Article 9): the same persons are not entitled to act as a transmission system operator and, at the same time, exercise control over an undertaking performing any of the functions of generation or supply of electricity (including sale or resale of electricity). Therefore, electricity generation and transmission must be performed by different companies. Likewise, the Directive requires the unbundling of distribution system operators (distributing electricity to end consumers), to guarantee independence of action from transmission system operators, supply of electricity, and generation (article 26).

According to the IEA (2012), EU electricity transmission systems will require 155 billion dollars (€115 billion) of investments up to 2035. The ongoing liberalisation of the energy market is expected to increase cross-border exchanges of electricity and also encourage the provision of electricity at competitive and more harmonised prices in the EU. This is supported by European Regulation 714/2009, which sets conditions for cross-border exchanges of electricity, through the creation of the European network of transmission system operators. However, even in the context of liberalised electricity markets,

[31] Note – this includes market-based operations, OTC operations and bilateral exchanges.

investments in electricity transmission may face practical problems and economic disincentives that can constitute barriers to investment, as reported by Frontier Economics and Consentec (2008). In particular, cross-border projects, which are essential to the functioning of EU electricity transmission network, may face the following difficulties:

- The planning and consents process needs to be undertaken in various jurisdictions, delaying projects;
- The additional flow of electricity across a new infrastructure will affect the wholesale prices of electricity in connected regions, whereas the cost of building the new infrastructure will most likely be borne by the users of the grid on which the asset is situated. This is a problem if paying users are not the ones who benefit most from the infrastructure in terms of decreased electricity prices; and
- There is a risk of low utilisation of the asset once it is operational, if market conditions which may depend on conditions in individual countries, do not encourage electricity exchanges through it.[32]

Within the context of this research this is relevant as each of these potential difficulties represent an area of risk or uncertainty that would be relevant to an investment decision.

Electricity distribution

Electricity distribution is the activity of distributing electricity to end users through medium to low voltage lines. It is the mechanism by which electricity is supplied to its end users (from generation, to transmission and then distribution). Distribution Network Operators perform asset management operations, network operations and customer relations.

According to IEA (2012), the necessary investments in electricity distribution to 2035 will amount to 688 billion dollars (€514 billion). Investments will be driven primarily by the need to replace ageing infrastructure, but also by the development of distributed energies networks and smart grids.

[32] Noting that a well known impact of interconnection is that local generators can choose to reduce prices to respond to a market threat from new importers and this may reduce the financial incentive for physical transfers.

3. Climate change and the electricity sector

The previous section set out some of the wider context for uncertainties relevant to investment decisions in the electricity sector across the EU. As discussed below, understanding weather impacts is part of the operation of the sector. The pertinent question however, is to what extent climate change impacts are understood. This topic is also explored in this section, considering the way relevant variables impact the operation of the sector and where there are areas of uncertainty associated with the impacts of climate change, relevant to electricity generation, transmission and distribution as well as demand.

The impact of weather on the electricity sector

Weather has an impact on the electricity sector, clearly seen in terms of fluctuations in demand and in the ability of the sector to generate and supply electricity efficiently. Variables such as wind speed, precipitation, temperature or solar radiation all have an influence on electricity production, transmission, distribution and consumption.

The performance of electricity generating facilities can be influenced by weather conditions, with sensitivity to different weather phenomena depending upon the type of generation. For example:

- Thermoelectric generation can be affected by cooling water availability and its temperature. One study estimates that, on average, 25 gallons (95 litres) of water are necessary to produce each kWh of electricity generated via the steam cycle (Bull et al. 2007). To provide cooling, nuclear power plants require reliable supplies of water within a specific temperature range;

- Power production from renewable sources of electricity depends on the absolute availability of renewable resources such as water, wind or solar radiation. In some parts of Europe snow melt is an important source of water for hydroelectric plants and facilities can be affected by a reduction in snowfall or a change in the timing of the melt season; and

- Flooding, whether flash flooding from storms or related to sea level rise as well as coastal erosion can put at risk the functioning of power plants as well as the viability of sites and may have additional impacts on safety concerns (e.g. for nuclear power plants).

For the electricity transmission network, hail, gale and lightning are considered to be amongst the most influential weather phenomena that can affect the reliability of power networks (Brown, 2002) and the frequency of lightning strikes has been shown to correlate with the frequency of outages (Zhou et al., 2006). In the United States, EPRI (2006) has estimated that 30% of power outages are related to lightning and costing utilities over 100 billion dollars annually. Similarly, Domijan *et al*. (2005) discovered that wind is one of the most significant factors affecting the total number of daily outages, followed by rainfall and moisture/dew. Furthermore, Yu et al. (2008) found that temperature variables have an impact on the economic performance of the UK's distribution network operators, even though they found that the magnitude of this impact was small on average in the special case of the UK.

More generally, all transmission and distribution networks are affected by high temperature which requires that some equipment must be "de-rated", reducing the amount of current they carry (Defra, 2012). Transmission and distribution networks are themselves also vulnerable to risks from flooding, particularly scouring of foundations and flooding of assets installed at ground level, such as sub-stations. Studies have shown that restoration time after power outages during winter storms is considerably longer than during normal weather (Wang and Billington, 2002). This may reflect concomitant impacts such as the event triggering the outage also hampering the ability of teams to reach the site of the outage and effect repairs as well as factors such as waterlogged ground reducing natural draining.

As regards electricity consumption, Defra (2012) note that temperature is often negatively correlated with electricity consumption because in the UK demand is predominantly related to low temperatures, primarily due to the heating load. However, high temperatures can also put more stress on electricity consumption due to the demand from use of cooling appliances (Hor et al., 2005), sales of which are projected to grow overall in Europe. In Spain, Pardo, Meneu and Valor (2002) have been able to estimate the influence of heating-degree days on electricity consumption with daily consumption and weather data. They found, similar to Peirson and Henley (1994), that the temperatures of previous days can also have an accentuating or an attenuating impact on the electricity consumption of the day implying that longer periods at a higher temperature may lead to the establishment of a pattern of higher demand.

The impact of climate change on the electricity sector

As climate changes, the expected change in the weather variables discussed above will introduce new challenges for electricity supply systems, from generation to electricity distribution networks. In the UK, Defra (2012) identified four main climate variables relevant for the electricity sector in the UK within the context of climate change: temperature, precipitation, wind and sea level. Although the Defra study focused upon the UK, the variables identified are relevant to the EU-27:

- **Temperature**: Projected change in temperature is one of the aspects of climate change where there is greatest confidence. With an increase in average temperatures, the number of cooling degree days is likely to increase while the number of heating degree days will decrease. This could shift the typical European seasonal pattern of electricity consumption from a winter to a summer peak. The European Environment Agency report on climate risk and vulnerability (EEA, 2012) presented a reduced demand for heating (particularly in northern and north-western Europe) but increased demand for cooling (particularly in southern Europe) as one of its key findings. Increased temperatures also have implications for generation capacity in that many power stations draw water for cooling from water courses. As temperatures increase, this becomes a less efficient process, with further limitations on the temperature of cooling water discharged (given the ecological damage that could be caused to receiving waters). Summer months are also the traditional time for maintenance work in the electricity sector but increased cooling demand may shift the window of opportunity for systems to be shut down;

- **Precipitation**: IPCC (2007) sets out the precipitation patterns projected for the future as climate changes, with a general drying in southern Europe and increasing levels of precipitation in northern Europe. This implies a potential opportunity for greater hydroelectricity generation in northern Europe but possible challenges for those in the south (depending upon design). More recent research has also shown that there is medium confidence that some regions of the world have experienced more intense and longer droughts, in particular in southern Europe (IPCC, 2012). Where there is a reduction in the water resource available, water for cooling power stations may not be available in sufficient volume for generation at full capacity throughout the year. There is also evidence of loss of snow cover and retreat of glaciers, altering the timing and volume of water available from snow melt. This has implications for the generation of hydroelectricity in some Member States. Changes in extremes rainfall, the high intensity rainfall events that occur over very short periods, also increase risk of surface water flooding in addition to the longer periods of rainfall that can increase flood risk generally. Assets, particularly in distribution networks given their density in urban environments, may then be at increasing risk from flood;

- **Wind**: Projected changes in wind climatology are highly uncertain and there is no significant trend emerging from observations gathered over recent decades. Thomas, Cox and Tindal (2009) have tried to analyse wind speeds to see if a pattern of change could be found from one year to the next in Northwestern Europe because of climate change. Their statistical analysis found no discernible pattern within the quite high variations of wind speeds. The IPCC (2007) also confirms that future projections of changes in wind climate are highly uncertain across Europe, although more recent work confirms that it is likely that there has been a pole-ward shift in the main Northern Hemisphere extra-tropical storm tracks (IPCC, 2012); and

- **Sea level**: sea levels are rising and, in a global average sense, will continue to rise in the future (as a combined result of thermal expansion of the oceans and melt of ice currently on the globe's land masses). It is likely that there has been an increase in extreme coastal high water related to increases in mean sea level (IPCC, 2012). The challenge is that regional patterns of future sea level rise are highly uncertain as they are heavily influenced by ocean dynamics and land movement (for example, northern parts of the UK are steadily lifting as a result of 'isostatic rebound' following the last ice age). Further, in some oceans there are thought to be areas where sea levels may actually fall in the future as a result of weakening or repositioning of ocean currents. As a guide, it is sometimes suggested that regional sea level could be plus or minus fifty percent of the global average (Hulme et al, 2002). Within the package of documents accompanying the EU Adaptation Strategy it is noted that energy production located in coastal areas may be threatened by sea level rise, storm surges and coastal flooding and that siting of future plant must take into account climate scenarios.[33]

[33] *Climate change adaptation, coastal and marine issue,* Accompanying the document "Communication from the Commission to the European Parliament, the Council, the European

These are only the main variables identified but there are others which are relevant. The Energy Networks Association (ENA, 2011) identified potential impacts on the distribution networks in the UK to be associated with wind and/or ice storms, lightning, heat wave and drought. As with the Defra (2012) study, these are impacts which, although identified in a UK study, are relevant across the EU.

The level of confidence in projections of changes in specific climate variables and how patterns of change will vary regionally are mixed. Even where long term trends are well understood and there is confidence in projections of future change, interannual variability means that some years could be much hotter, colder, wetter or drier than average, introducing a degree of uncertainty. How the changes in climate variables could interact with the electricity system is also a very complex issue adding to the challenge of determination of future demand as well as prices and costs. For example, higher temperatures may increase demand due to air conditioning or reduce it due to lower heating requirements.

According to Defra (2012), climate change will mean interconnected risks for electricity security and for investment costs in the UK energy sector, including:

- Power supply disruption and asset deterioration (e.g. due to increased fire hazard from changes in carbon-based fuel moisture content, increased overheating of energy industry buildings);
- Variation of renewable energy resource availability and output (solar radiation, water, etc.);
- Potential reduction of efficiency in power station outputs (e.g. lower cooling efficiency of warmer water) and power transmission (e.g. cables affected by temperature changes); and
- Changes in energy demand patterns, possibly reducing total energy demand due to a lesser need for heating, but also increasing the risk of the impact of demand peaks exceeding grid capacity.

Economic and Social Committee and the Committee of the regions: An EU Strategy on adaptation to climate change", SWD(2013) 133 final

The same report also sets out risk of flooding for electricity substations and other energy infrastructure located in vulnerable areas noting: "*The number of power stations at risk of flooding in England and Wales is projected to rise from 19 today to 26 (21 to 27) in the 2020s to 38 (31 to 41) in the 2080s.The risk of flooding to major substations is projected to rise from 46 today, to 53 (48 to 60) by the 2020s and 68 (57 to 79) by the 2080s*"[34]. It is unlikely that this risk applies only to the UK although it would not be advised to take this as indicative of risk for other Member States as rainfall changes and flood risks will not be homogeneous across Europe (as noted previously).

A study by Vine (2008) also discussed how climate change will affect power generation, in particular from hydroelectric plants because reduced water flows will be available at peak demand periods in summer and also because water scarcity will create additional stress on regional water management. Although this particular study was undertaken in California, the results can be taken as analogous to Southern Europe and are more widely applicable in Europe as expected changes to the cycles of snow and rainfall will have similar impacts. Early snow melts and heavy stream flows could force engineers to release water from reservoirs and divert water from hydropower facilities in order to avoid flooding and damage to the installations. The timing of snow melt peaks in the cycle of annual water resources is a key input to hydropower generation calculation in alpine areas. There are indications that since the 1970s, annual energy production of some existing hydropower stations in Europe has decreased, in particular in Portugal, Spain and other Southern European countries (UCTE, 1999). Although this reduction has been attributed to changes in average discharge, it is not known if this is a consequence of climate change (Lehner et al., 2001), even if it appears consistent with climate projections. Conversely, it has also been suggested that the potential for hydroelectricity generation in Nordic countries will increase as a result of projected change in climate (Golombek *et al.*, 2012).

Climate change and uncertainty for the electricity sector

In the context of the electricity sector, climate change uncertainty has most impact on assets with long lifetimes, such as energy generation and transmission infrastructure which

[34] The ranges in the figures reported by Defra (2012) result from the different climate change scenarios used within the study, i.e. 21 cm under the low emissions scenario, 26 cm under medium emissions and 27 cm under high emissions by the 2020s, etc. The projections used are the UKCP09 Climate Projections for the UK.

may have operational lives of 50 years or more (noting that the same observation applies to many other sectors including for example transport and the built environment). The further into the future that is considered, the greater the uncertainty in climate projections because the future evolution of GHG emissions is not known, hence the use of scenarios. Further, climate projections begin to diverge after the middle of the century depending on the GHG scenarios used, (i.e. the difference between the low and high emission scenario becomes more significant). This introduces another element of risk. Where assets have a shorter lifetime, routine replacement programmes provide opportunities to increase resilience periodically in the future. With longer lifetime assets, there is a risk of "locking into" a design solution which may not provide long term resilience.

Adaptation reports from utility companies in the UK (as a commitment under the UK Climate Change Act (2008)) set out the aspects of climate change which can be linked to vulnerability, or risk, and present a view of the levels of uncertainty associated with each. These reports, although part of the same overall package as the Defra report on climate risks to the sector (Defra, 2012) were developed independently by utility companies without sight of the Defra report. It is interesting to note that the Defra report highlighted four main climate variables but that the industry owned studies identified others. The additional factors considered in the adaptation reports include:

- Increases in the frequency of lightning;
- Increases in wind speeds and occurrence of gales;
- More occurrences of snow, sleet, blizzards, ice and freezing fog;
- Increase in both coastal and river erosion; and
- Increased risk of subsidence where soils are susceptible.

Changes in wind and lightning were highlighted as two of the more significant areas of uncertainty with a lack of information (for these variables) in the scenarios of climate change. This was summarised in the adaptation report from National Grid – Electricity (2010) which details a number of gaps in industry knowledge about the risks associated with climate change, derived for the main areas of uncertainty in climate projections for the UK. Similar observations have been made by other utility companies in their own reports but National Grid identified that:

- There is no information available on future changes in the frequency or intensity of wind and gales. This includes a lack of information on the likelihood of a period of low wind speed (dead calm) coinciding with a period of high ambient temperatures, conditions that increase the challenges of supplying energy to customers as demand increases at the same time as risk to the network;

- There is no information on future changes in the frequency or intensity of lightning. Transmission and distribution systems are particularly vulnerable to lightning but climate models are not able to provide projections of likely changes to lightning (due to resolution) so this remains one area of significant uncertainty; and

- There is limited information on the frequency and intensity of snowfall and accumulations and no information on the likely frequency of ice and freezing fog, conditions which can make overhead lines vulnerable to damage.

These observations, although specifically for the UK, are relevant for the whole of Europe. There is a lack of consistency in the projected changes to the future wind climate and a lack of confidence in the future frequency and intensity of storms. Changes in storm frequency in Europe show no clear overall trend, with a general increasing trend being observed from the 1960s to 1990s, followed by a decrease to the present (EEA, 2012). Research has however suggested a shift in the storm track may be likely, with a weakening of the Mediterranean storm track and a strengthening of the storm track north of the British Isles (Bengtsson et al, 2006) although there is currently no consensus on this point within the research community.

Figure 3.2 visualises the differences between risk and uncertainty across the electricity sector associated with climate change. For example, based on the definition of Knight (1921) as set out in Box 3.1, projected changes in temperature pose a risk to all parts of the electricity sector as each element (generation, transmission and distribution) are vulnerable to temperature increases.

Box 3.1: Defining uncertainty and risk
Uncertainty can be defined as the information gap which impedes the simple calculation of expected prices, costs and amounts of electricity transmitted or generated. Following the work of Knight (1921), economists usually distinguish between risk and uncertainty. Under **risk**, the set of probabilities that may lead to different outcomes is known. For example, based on past evidence and assuming no change in average wind speed, it is possible to estimate the expected frequency of days with high wind speeds and days with low wind speeds for a specific location. Using the probability that wind speed is high or low, it is possible to calculate expected electricity generation by a wind turbine and derive expected profitability and other related variables. Use of the probability allows risk to be managed for the location and a calculation of a most likely cash flow is possible. On the other hand, climate change may impact wind speeds but in ways which are much more uncertain leading to changes in wind speed, direction or extremes. For this range of potential change, a probabilistic approach to risk may no longer be valid.

However, because of confidence in projected changes of temperature, there is relatively little uncertainty. Conversely, all parts of the sector are vulnerable to storms, gales and strong wind but there is very little information in future projections making this a key area of uncertainty. For precipitation which could result in flooding, larger electricity generating plants are often assessed for flood risk and the likelihood of a flood impacting the site is thus understood. Flooding is therefore a risk but there is limited uncertainty. However, uncertainty associated with flooding increases for transmission and distribution networks because they are less likely to have been flood risk assessed (in part because of the number of assets within the networks). Further, flash flooding due to surface run off is more common in urban environments and this is where the majority of distribution network assets are located. There is significant uncertainty associated with this type of flooding however as it is due to very localised and intense rainfall.

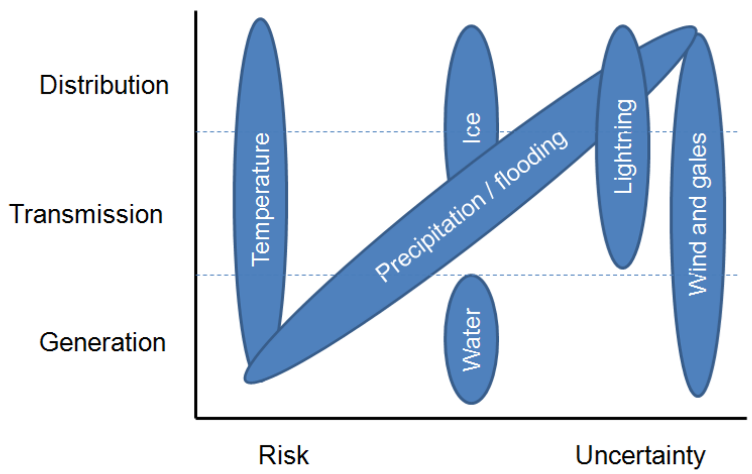

Figure 3.2: Schematic of risk versus uncertainty associated with climate change across the electricity sector

Climate change can add uncertainty and risk to investment costs in electricity infrastructure but it may also be that investment which includes an adaptation measure to manage the potential impacts of climate change will have only marginal additional cost or that a behavioural/management change (with no additional costs) will be sufficient to address the risk. For example, where a nuclear facility is to be constructed in a coastal location, the platform upon which the site is constructed needs to be at a height above sea level considered to be free of risk of inundation and coastal flooding. Any additional height required to address uncertainty in regional patterns of sea level rise will increase overall investment cost at the time of construction but this may be small compared to the cost of making the site resilient later. More generally, investment decisions which do not take into account climate change, and the uncertainty associated with it, risk requiring additional investment in the future. In a worst case scenario, an investment where climate change and the associated uncertainties are not considered could become inoperable before its full potential life cycle is complete. One example would be development of an asset which requires significant water inputs in a region where drought is likely to occur more frequently in the future. Key is to avoid locking into an asset design which provides no option for future adaptation. In this context, Defra (2012) recommends that considerations of climate change should be taken into account in relation to known weather sensitivities, so that maintenance programmes, for example, will not compromise electricity supply during extreme weather events.

Understanding of climate impacts on the electricity sector across the EU is increasing. A recent report by the European Environment Agency (EEA, 2013) states that "*According to the information submitted by the EEA member countries, a total of 16 countries have already adopted national adaptation strategies, and 12 others are currently in the process of developing them*". Of those who have already adopted a national adaptation strategy, the majority (Finland, UK, Portugal, Spain, France, Denmark, Switzerland, Austria, Germany and Lithuania) highlight the energy sector as a priority area within the strategy. That is not to say that the others do not identify energy as a vulnerable sector however. Hungary has indicated that critical infrastructure will be one of the priority themes in the revised national adaptation strategy. Sweden assessed risks to energy systems in its vulnerability assessment. Other strategies take a non-sectoral approach, considering adaptation as a cross sectoral issue. Further, some Member States have studies and assessments of vulnerability of the energy sector where an adaptation strategy has not yet been adopted. The EEA report identifies energy sector actions in the plans of 14 countries (this includes those plans in development). An example of a Member State adaptation action plan for the sector is given in Box 3.2 below.

Box 3.2: French Adaptation Plan – Energy and industry action sheet[35]
Action n°1: Manage the emergence of peaks in summer energy consumption via an electrical capacity obligation mechanism Cold spells usually trigger consumption peaks. A planned capacity obligation established in this context would also be adapted to peaks in hot spells (linked to cooling requirements). It would safeguard continuity of supply available for use. **Action n°2: Promote the use of more efficient cooling equipment (air conditioning) or equipment using renewable or recoverable energy** Pursuing mechanisms for Energy Saving Certificates (ESC) and the adoption of a 3rd period will encourage people to replace the most energy-intensive cooling equipment and promote renewable energy sources such as geothermal energy. The Heating Fund will back collective cooling projects using renewable or recoverable energy, which will mean fewer pressures on the network during hot weather. **Action n°3: Make all hydrogeological and climate data available** This request, which emerged from the consultation exercise, will be met by the implementation of a national water data plan. This will improve the quality of data available online on the Eau France knowledge-sharing portal. Climate data and regional projections will be available from 2012. **Action n°4: Integrate climate change into the monitoring indicators of the Framework Water Directive** Long-term monitoring of the status of bodies of water within the FWD is an important tool for observing the effects of climate change. This permanent observation process should be able to isolate disruptions attributable to global warming from those caused by industrial activities using water for cooling (notably electricity generation plants). The permanent network, which will be introduced in 2012, will integrate this aspect of climate change into the indicator monitoring process. **Action n°5: Identify French industrial sectors which are vulnerable to climate change and potential opportunities (2030-2050)** Several economic sectors (agriculture, forestry, energy generation, tourism, transport, etc.) are positively or negatively affected by changes in the climate, depending on the case. The industrial sector is very important for the national economy and the balance of trade, but to date there is little evidence available about its vulnerability to future climate change. This action aims to evaluate the sensitivity of this sector to climate change and the implications in terms of economic intelligence at a national level for a 2030 and a 2050 horizon.

4. Drivers for investment in the electricity sector

Within this section, a range of the drivers for investment and how this influences decision making are considered. The types of potential investors, challenges, opportunities, EU (and Member State) policy and the constraints of investment in a regulated industry all influence decision making.

As an example, for the Connecting Europe facility, it is estimated that approximately €200 billion of investment is needed for electricity and gas networks (in combination) of European

[35] French National Climate Change Impact Adaptation Plan 2011 – 2015, http://www.developpement-durable.gouv.fr/IMG/pdf/ONERC_PNACC_Eng_part_1.pdf

importance alone. €100 billion of this investment should be delivered by the market unaided, whereas the other €100 billion will require public action to leverage the necessary investments.[36] In public-private partnerships, particularly for development of new generation capacity, the driver for public bodies is most likely to be energy security while the private sector partners will most likely decide to invest (or not) based on a profitability assessment which considers financial flows from the project planning phase through to the end-of-life of the asset, in particular the income that can be generated versus the capital costs and operating costs (including fuel and maintenance). For many investments in the sector, the investment must be approved by the regulator in the Member State, with application based on a business case which includes appropriate consideration of such costs and benefits (often assessed over a set period of time which may not take account of climate change horizons).

As discussed previously, the IEA have estimated that over €1 billion of investment will be required across the energy sector in the EU over the next two decades if EU targets for decarbonisation of the sector are to be met by 2035. This is a significant driver for investment but there are a range of barriers associated with investment in electricity generation. Any form of barrier can represent a risk or uncertainty in the investment decision as it may affect return on investment, development timescales and costs, successful installation of the proposed infrastructure, etc. For example, there is a need for significant investment in renewable energy technologies identified but challenges relating to public opinion, connecting to the existing grid, gaining appropriate consents and permits, etc., can be seen as potential barriers. The fact that investment continues to be made in renewable energy suggests that the sector already overcomes such barriers (and therefore uncertainties) in decision making processes for investment.

There are other risk and uncertainties associated with meeting the decarbonisation targets of the sector. Distributed technologies, such as integrated deployment of small and medium scale renewable electricity generation, can face barriers to their uptake as a result of network effects. Put simply, connection needs to be made from the new asset to the existing grid and there is a cost incurred in doing so, both in terms of the cabling but also in gaining appropriate permissions along the route. Although this is a transmission and

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36 http://ec.europa.eu/economy_finance/financial_operations/investment/europe_2020/investment_needs_en.htm

distribution constraint, it has the potential to restrict investment in generation infrastructure as there is uncertainty in whether connection to the grid will be possible (a factor also linked to accessing financial incentives for investment in specific technologies). Bruckner, Morrison and Wittmann (2005) studied the importance of network effects and network externalities to better understand energy planning with distributed technologies. Paradoxically, such technologies *may* be profitable only if interconnected infrastructure is already in place before any investment is made, for example adding to existing networks rather than establishing a new one or installing district heating only where a suitable source of low carbon energy/heat already exists and there is a demand for the heat it provides. This is particularly relevant in that smart grids are designed to facilitate integration of distributed technologies and so any development of a smart metering programme, when combined with a smart grid, can facilitate investment in distributed technologies.

To promote electricity generation from renewable sources, Member States have put in place feed-in payment (or tariff) systems, quota obligations with tradable green certificates, investment grants and tax incentives (Ragwitz et al., 2012). At Member State level, one of the most commonly used policy options for the support of renewable sources of energy are feed-in systems with 20 out of 27 MS using them to support the development of renewable sources of energy (see Figure 3.3). Two kinds of feed-in systems can be implemented, either Feed-in tariffs which guarantee a fixed price per kWh of electricity or Feed-in premiums which guarantee a fixed premium per kWh of electricity, paid additional to the market price of electricity.

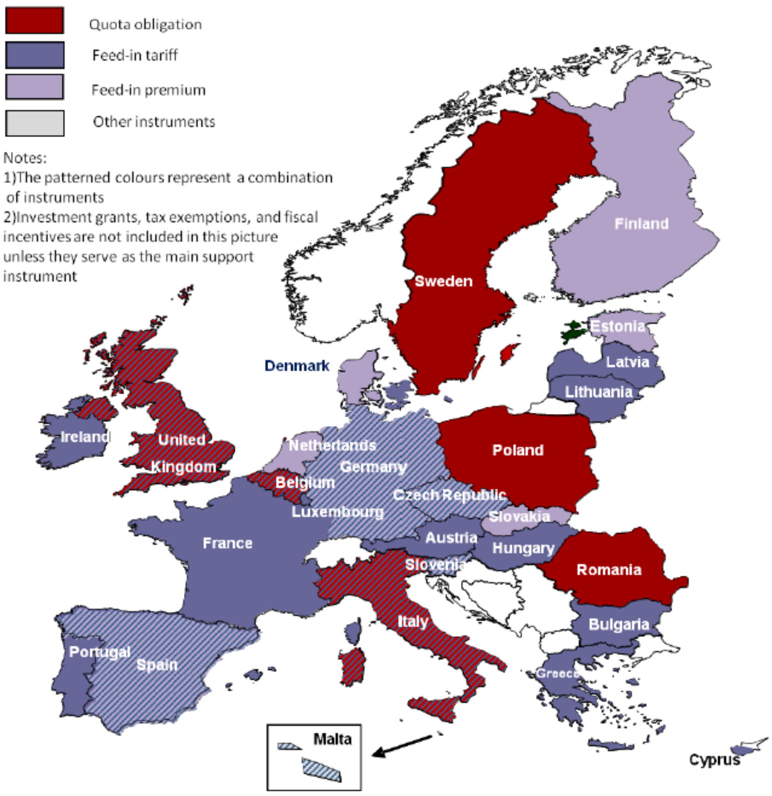

Figure 3.3: Map of EU countries according to their support mechanism of renewable sources of energy (Ragwitz et al., 2012)

5. Decision-making methods under uncertainty applicable to the electricity sector

As well as uncertainties related to physical factors, such as changes in wind climatology, climate-related factors are part of a wider picture of risk and uncertainty:

- **Capital costs** can be subject to the uncertainty of construction cost escalation. This phenomenon has been observed, for example, during the construction of nuclear power plants and has been documented in the US for example (Hultman, Koomey and Kammen, 2007). This particularly applies to generation as the scale of investment is typically larger than for transmission or distribution assets but the effect does apply across the sector (as it does in others such as transport, etc);

- **Operating costs** are subject to uncertainty in unpredictable maintenance costs or risk of price increase of inputs, such as fuel prices for a coal-based power plant. This is relevant across all parts of the sector. One example associated with transmission and distribution networks is the likely requirement to increase the frequency of vegetation clearance, including cutting back trees in order to make sure overhead lines clearances are maintained;

- **Price** have many kinds of risks and uncertainties[37] from the daily fluctuations of electricity prices in the wholesale market to, more structurally, factors such as the uncertain evolution of supply and demand in the long run. Furthermore, future climate change mitigation policies and the way they are reflected in electricity prices is an unknown parameter to investors that results in additional price uncertainty (Ming et al., 2008). This could impact all in the electricity supply chain, from generation to distribution, given price is so closely linked to income derived from electricity supplied to customers; and

- **Quantity requirement** are subject to the overall variation in expected demand dependent on structural factors such as use of electric vehicles but may also be affected by strategies adopted by other suppliers and their expectations, for example the degree to which they invest in solar energy. This impacts all parts of the supply chain as it is a capacity issue, either providing adequate capacity in the distribution network to accommodate distributed technologies or through the total of energy generated to meet demand (and the infrastructure required to supply it).

A common classification of the existing models for investment decisions in the electricity sector is based on the planning horizon of the decisions to be made. Short term planning deals with very short time horizons of supply adjustment, typically over one week or less. Medium term planning deals with decisions over a 1-3 year period, whereas long term planning typically has a horizon of more than 15 years (Wallace and Fleten, 2003).

For long term electricity planning, the use of data management and modelling techniques is common using both technical and economic factors. Wallace and Fleten (2003) present a general framework for profitability assessment of long term investments, such as the building of thermal units or the construction of hydro reservoirs and turbines. They explain that the starting point of this kind of assessment is the projection of future expected load and, in practice, the consequences of a wrong assessment of this expected load can be significant. For example, an underestimation of electricity demand by a retailer may lead to

[37] In the case of feed-in tariffs, price uncertainty is not faced by investors in renewable electricity generation as the price of electricity is fixed by contract.

higher than expected operational costs because the additional demand has to be met by purchasing additional amounts of electricity at a high price on the wholesale market. As load forecasts for the electricity network affect electricity transactions on the futures market, they can have a significant impact through wholesale futures prices on all the actors in the electricity sector from producers to end consumers. Financial incentives, such as Feed-in-Tariffs, can however provide some certainty as a price is fixed for the duration of a contract (as discussed earlier).

Tools employed to forecast load include regression and time series analysis, but also methods belonging to the fields of artificial and computational intelligence (Hahn, Meyer-Nieberg and Pickl, 2009). Regression and time-series analysis are classical methods of statistical analysis based on explicitly formulated mathematical models which estimate the relationship between load and various input factors such as weather, demography, economic growth, etc. Once such a relationship has been estimated, it is possible to forecast electric load based on reasonable assumptions about how input factors may evolve in the future. Methods from artificial and computational intelligence are drawn from a research field that is relatively new but has shown some promise for electric load forecasting. Within these methods, neural networks are the most frequently used method for load forecasting. The basic working principle is interconnection of nodes that treat and aggregate information to formulate appropriate responses.

A simple approach to taking risk or uncertainty into account is through the development of various scenarios with the same forecasting technique. In the case of regression analysis, this can be done by making different assumptions about future trends of input parameters (e.g. economic growth, input fuel prices, etc.) so as to calculate the output value of the parameter of interest (electric load in this example) for the forecasts. Such probabilistic analyses are widely used in the electricity sector, for example by utilities in their planning and operation studies (Gorenstin et al., 1993). However, probabilistic techniques may or may not consider many kinds of uncertainties and in practice many parameters are still represented as deterministic. Gorenstin et al. (1993) notes that the following parameters that are often represented as deterministic, rather than probabilistic, ones:

- Load growth rates;
- Fuel costs;
- Construction time;

- Interest rates and financial variables;
- Economic growth; and
- Environmental constraints.

Instead of weighting different scenarios with probabilities based on deterministic representations of uncertain parameters, uncertainty can also be taken into account during the development of non-deterministic scenarios (using stochastic programming methods), noting that taking into account uncertainty during the development of scenarios will almost always lead to different solutions than developing deterministic scenarios and making a weighted average over these scenarios. This is because, for each scenario that, by construction, does not take into account risk or uncertainty, the optimal solution that is identified will assume perfect knowledge of future events. Such solutions will therefore never lead to consideration of flexible options in case extreme events might happen because these eventualities are not taken into account (by construction) in the modelling exercises. On the other hand, when scenario development integrates risk or uncertainty, then the optimal investment decision as identified by the techno-economic tools takes into account the need to be responsive in case of an incident.

Stochastic programming in energy includes a wide range of methods that take into account the unpredictability of future events (including quantities, prices which are volatile, etc.). Some sophisticated models take into account the possibility of selling electricity on the futures market and medium term price expectations. Other models try to assess the evolution of the electricity market as a whole. These models have been useful to generate long term electricity price scenarios (Wallace and Fleten, 2003).

Furthermore, and because decision-making under uncertainty must take into account many different factors (not only economic, but also technical, social and environmental), the use of multiple criteria decision-making (MCDM) has developed for investment decisions in the energy sector.

In their demonstration of a MCDM method for a theoretical case study of distribution utility investment planning, Espie et al. (2000) took into account the following criteria: expenditure; profitability; quality of supply; customer service; and environmental benefits. On the other hand, for electricity planning in Spain, Linares and Romero (2000) took into account total cost, CO_2 emissions, SO_2 emissions, NOx emissions and radioactive waste produced. Linares and Romero (2000) also constrained their model to take into account demand requirements; resource availability; limits to technologies; domestic fuel quotas; energy security; and the constraint on power generation with installed capacities. In the end, MCDM methods have the advantage of taking into account many elements that may not be fully taken into account in more financial profitability assessments. However, the accuracy of such methods actually depends on the weighting strategy: with different weights, MCDM may provide different rankings of the options under study.

With these methods, uncertainty can be taken into account by making a sensitivity analysis of the best option for different uncertain parameters. Other potential approaches are based on different statistical techniques to maximize welfare, although the literature review did not identify evidence of their use in the electricity sector. One example of this is the "maximin regret criterion" presented and employed by Espie et al. (2000).

Following Aaheim and Bretteville (2001), it is possible to identify five alternative decision-making criteria, including the one used by Espie et al. (2000), which can be applied under uncertainty. These criteria can be applied to various kinds of decisions and in the presence of two or more alternatives:

- **The "maximin" criterion**: the maximin criterion ranks all the potential alternatives according to an evaluation of their worst outcomes. Consequently, an alternative is considered superior to another when its worst outcome is less catastrophic that the worst outcome of the other alternative. This decision rule allows worst-case scenarios to be avoided;

  The criterion of "generalised maximin and maximax": this decision rule first estimates the best and worst outcomes of each option, and then makes weighted sums of the best and worst outcomes. Like "maximin", this decision criterion gives high importance to preventing worst-case scenarios. However, it also takes into account that each option may provide benefits that should be taken into account. All in all, the relative weight given to worst outcomes and best outcomes captures the investor's risk aversion. In the maximin framework, risk aversion is absolute and no weight is given to the best outcomes;

- **The criterion of "limited degree of confidence"**: under limited degree of confidence, the decision-maker tries to calculate profitability by using the "maximisation of expected utility" criterion (based on a broad probabilistic assessment). However, he knows that he should have limited confidence in the outcome. Therefore, he also applies at the same time the “maximin” criterion, and makes a weighted sum of the outcomes obtained with both criteria;

- **The “maximin regret” criterion**: with this criterion, the decision-maker answers the question: “With which option, if I make a mistake, will I regret less?” The decision-maker therefore calculates the “regret” that he/she could have if he/she was not to take the right decision. Such a “regret” is calculated as the difference between the outcome of the chosen option and the best outcome that could achieved with a different decision being taken. This “regret” of making a specific decision is to be calculated for each potential state of future events, taking always as a reference the best decision that could be taken. Once the “regret” of choosing a specific option has been calculated for all potential events, it is possible to calculate what the maximum value of the regrets is for this specific option. By doing this same calculation recurrently for all possible decisions that could be made, it is possible to identify which decision has minimum negative impact if it ends up being a wrong decision; and

- **The criterion of “safety first”**: this decision-making criterion consists in choosing the option that minimises the probability that the outcome could be inferior to a given threshold. This threshold consists of a “safety net” that the decision-maker wants to ensure.

Such techniques have been applied to scenarios in the energy sector by the research community, demonstrating their potential. Examples include:

- Alanne et al. (2007) which applies multi-criteria decision-making to the choice of a residential energy supply system: they compare micro-generation heating systems with traditional heating systems, and consider various decision rules, including maximax, maximin and minimax regret; or

- Gnansounou et al. (2004) which develops an agent-based model designed to support decentralised planning activities in the electricity supply industry, where the decisions from investors can be triggered by alternative decision criteria such as maximin, to take into account the uncertain context of decision-making.

Tools for decision making relating to climate change.

All of the techniques described above, which are capable of dealing with uncertainty, can be embedded into an iterative process of making and revising decisions. One example of an interactive process is the UK Climate Impacts Programme (UKCIP) decision making under uncertainty framework tool which provides a flexible approach to decision making under climate uncertainty. It is comprised of eight stages (see Figure 3.4 below) based upon the principles of good decision making. It is cyclical, with emphasis on an adaptive approach where decisions are revisited when new information on climate change and its impacts are published. As well as reducing uncertainty and increasing accuracy, the feedback and iteration in the stages aids the refinement of the problem, objectives and decision making criteria, which are important in achieving solid decisions. There are also tiered stages (3, 4 and 5), which allow the decision maker to identify, screen, prioritise and evaluate climate and non-climate risks and options before a decision is made on further detailed assessments or appraisals are required (Willows and Connell, 2003).

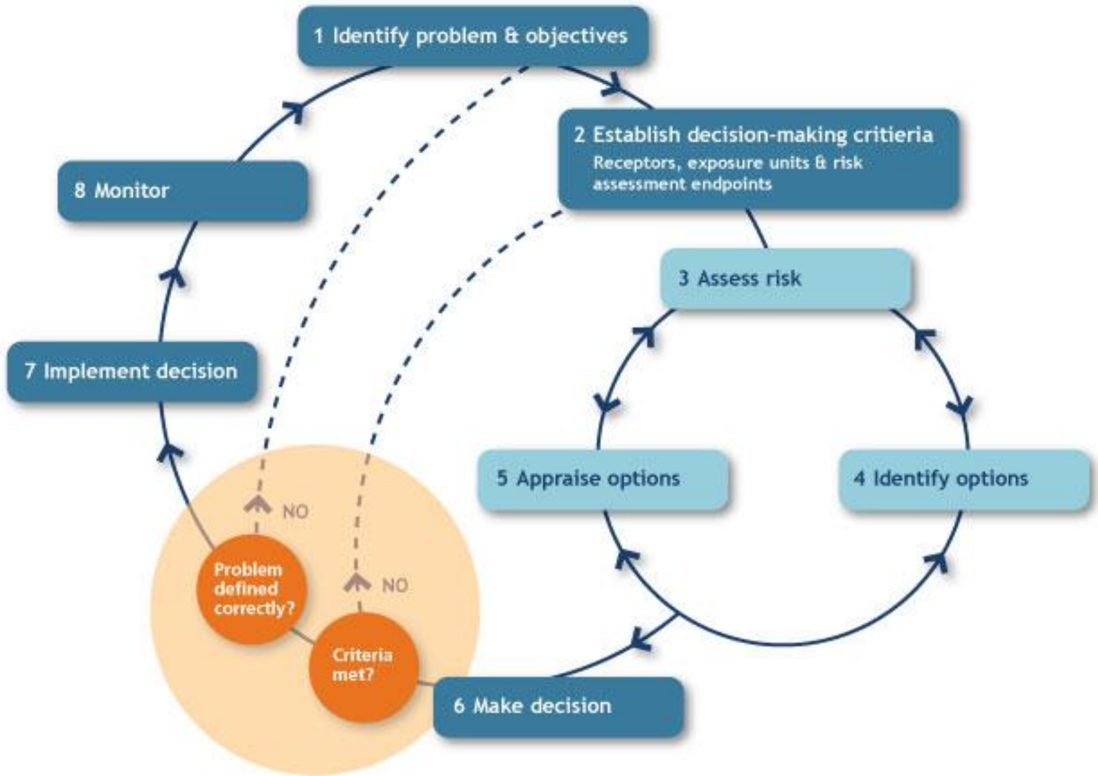

Figure 3.4: A framework to support good decision-making in the face of climate change risk (Willows and Connell, 2003)

Under uncertainty, it is common to make additional precautions in the eventuality that 'bad' events might occur, even after choosing the best investment decision available. The U.S.

Climate Change Science Program (2009) notes that the application of the "precautionary principle" is a strategy often proposed for use under high levels of uncertainty. The precautionary principle *"enables rapid response in the face of a possible danger to human, animal or plant health, or to protect the environment. In particular, where scientific data do not permit a complete evaluation of the risk, recourse to this principle may, for example, be used to stop distribution or order withdrawal from the market of products likely to be hazardous"*[38]. However, the precautionary principle may not lead to optimal decision-making in relation to the impacts of climate change. The U.S. Climate Change Science Program (2009) identifies two kinds of strategies considered likely to outperform it:

- **The resilient strategy**: the principle is to identify the range of future circumstances that one might face, and then look for approaches that will work well across this range. An example of resilient strategy is presented by Hallegatte (2009) and relates to water management in Copenhagen. To manage risk arising from projected increases in precipitation, water managers in Copenhagen took a safety margin: "to calibrate drainage infrastructure, water managers in Copenhagen now use run-off figures that are 70% larger than their current level. Some of this increase is meant to deal with population growth and the rest is to cope with climate change, which may lead to an increase in heavy precipitation over Denmark." Similarly, Western Power Distribution in the UK examined future flood risk using climate change scenarios when replacing major substations on flood plains. After considering a range of options, they found that the marginal cost of considering the flood risk management solution at the same time as normal asset replacement activity proved to be substantially cheaper than other functional equivalent options (Western Power Distribution, 2011) ; and

- **The adaptive strategy:** the idea is to make decisions that are flexible enough to be modified if necessary as more information is gathered and uncertainty reduces. Hallegatte (2009) gives the example of insurance and early warning systems that can be adjusted each year with new information. A classic example of the use of flood defence barriers which can be increased in height over time if and when required.

These strategies, used in synergy with climate projections and decision making tools, can help make better decisions under uncertainty. For example:

[38] Communication from the Commission of 2 February 2000 on the precautionary principle, COM(2000) 1 final, http://ec.europa.eu/dgs/health_consumer/library/pub/pub07_en.pdf

- Investment options can be designed in such a way that they adopt resilient and/or adaptive features;
- For these investment options, decision-making can look at the many aspects of complex investments through the use multiple criteria decision-making or sophisticated forecasting tools; and
- The criteria used to finally make a decision can be selected taking account of high uncertainty, potentially high losses or opportunities.

6. Conclusion

Investments in electricity generation, transmission and distribution depend upon many factors even before the consideration of climate change. Therefore, climate change will be an additional parameter to be taken into account when assessing the profitability of electricity generation, transmission and distribution infrastructures. Taking into account this additional parameter will be much more imperative for investments with longer lifetimes, as they put investors more at risk of "being locked in". For the investments with shorter lifetimes, the possibility should be seized of frequently adapting infrastructures to up-to-date knowledge about climate change.

Besides, our knowledge of the future impacts of climate change on the electricity sector is uneven and has to do with our knowledge of climate change, with is more precise when it comes to temperature and precipitations than when it comes to wind and lightening. However, there is a wide range of techniques available and employed in the electricity sector, whether in generation, transmission and distribution, to manage uncertainty in decision making. These techniques can be applied to consider climate change and adaptation. This suggests that it is not necessarily the technique of decision making that needs to change if climate change is to be considered in investment decisions, given the level of experience in the sector of both understanding the impact of weather of its systems/networks and in managing uncertainty. As shown, there are other tools which have been applied in theory and could be incorporated into decision making processes however there are also examples of effective use of existing approaches and information. The challenge is thus making sure that there is appropriate awareness of methods and tools and that the sector has access to the right information to enable it to move towards greater climate resilience.

Chapter 4: Adaptation to Climate Change and US Residential Energy Use – Does Adaptation Reduce Greenhouse Gas Emissions?

François Cohen, Matthieu Glachant and Magnus Söderberg

Abstract

Previous literature has found that positive temperature shocks increase US residential electricity consumption because air-conditioning is used to adapt to excessive heat. This suggests that climate change adaptation could increase electricity demand. This research goes beyond previous analyses by evaluating which drivers would explain the relationship between climate change and energy use. We look at the alterations and improvements to housing associated with climate shocks – including but not limited to air-conditioning – and correlate these changes with both gas and electricity consumptions. Then resorting to a long-term simulation, we find that climate change is likely to increase residential electricity consumption. However, this surge in electricity consumption could be more than compensated by a parallel decrease in gas consumption. All in all, residential energy consumption (adding gas and electricity consumptions) could decrease due to adaptation to climate change, but not necessarily greenhouse gas emissions. Electricity generation in the US is carbon-intensive so that the predicted shift from gas to electricity could sustain greenhouse gas emissions in spite of a total reduction in energy demand resulting from climate change. This puts pressure on decarbonising electricity generation.

Keywords: Climate change adaptation, home improvements, residential energy consumption.

JEL Codes: D12, Q47, Q54, R22.

Résumé du chapitre 4 en français

Des études précédentes ont établi que les hausses de température augmentent la consommation électrique du secteur résidentiel américain, très vraisemblablement parce que l'air conditionné est utilisé par les ménages pour s'adapter à la chaleur excessive. Cela suggère que l'adaptation au changement climatique pourrait accroître la demande électrique aux Etats-Unis. Cette recherche va au-delà des analyses précédentes en identifiant plus précisément les mécanismes qui expliquent la relation vraisemblable entre changement climatique et consommation d'énergie. De ce fait, nous nous penchons sur les altérations et les améliorations des habitations qui sont associées aux chocs climatiques – qui incluent l'air-conditionné mais n'y sont pas limitées – et les mettons en relation avec l'évolution des consommations d'électricité et de gaz. En recourant à une simulation de long-terme, nous trouvons que la consommation électrique du secteur résidentiel est plus élevée dans un scénario avec changement climatique que dans un scénario où les températures demeureraient constantes. Cependant, cet accroissement des consommations électriques pourrait être plus que compensé par une réduction parallèle des consommations de gaz. Au total, la consommation énergétique du secteur résidentiel américain pourrait baisser du fait de l'adaptation au changement climatique, mais cela n'entrainerait pas nécessairement une même réduction des émissions de gaz à effet de serre associées à la consommation d'énergie. La production d'électricité est intensive en carbone aux Etats-Unis de sorte que le basculement d'une consommation au gaz vers une consommation électrique pourrait soutenir les émissions de gaz à effet de serre. Nos résultats mettent donc l'accent sur le besoin de réduire l'empreinte carbone de l'électricité.

1. Introduction

Climate has already changed and most experts believe the global average temperature will continue to increase: the fifth report of the Intergovernmental Panel on Climate Change (IPCC, 2013) estimates that global mean surface temperature could be up to 4.8°C higher in 2081-2100 relative to 1896-2005 if greenhouse gas emissions (GHG) continue unabated. Climate change will affect human activities through many channels, including agricultural production, labour productivity, industrial output, health, energy or political stability.[39] In a world cross-section, Dell, Jones and Olken (2009, 2012) estimate that national income falls by 8.5% per degree Celsius. In poor countries, these authors find that a 1 degree Celsius rise in temperature reduces per-capita income by 1.4%.

However, acclimation can reduce the impact of high temperatures on human activities. In this direction, Dell, Jones and Olken (2009) compare the long-run consequence of temperatures on economic output with the short-run negative impact of temperature shocks. It appears that short run impacts are much sharper than long run impacts, suggesting that the negative impact of temperatures on output is compensated for by adaptation measures in the long run. More precisely, these authors find that nearly half of the negative impacts of high temperatures on income are cushioned by adaptation measures in the long run.

For future global warming, this suggests that adaptation may reduce the impacts of ongoing climate change on human activities to a large extent. A concrete example is given by Barreca *et al.* (2013), who find that the progressive adoption of air conditioning throughout the 20th century explains 90% of the entire decline in the temperature-mortality relationship in the US.

Interestingly in this case, adaptation is also unlikely to be neutral in terms of GHG emissions: air-conditioning may not only be very effective as an adaptation to excessive heat, it is also particularly energy consuming. In these lines, Sailor and Pavlova (2003) predict that market saturation of air-conditioning could increase drastically with climate change and be more important as a driver for future energy load than the sole impact of temperature shocks. Focusing on 38 US cities, they forecast that a 20% increase in cooling degree days would

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[39] Dell, Jones and Olken (2013) make a thorough review on the economy-climate relationship.

increase residential electricity consumption by 1-9% depending on the city, mainly driven by a 20-60% increase in electricity consumption from air-conditioning.

More generally, adaptation will require additional investments of different types: dikes to prevent from sea level rise, changes in crop-management practices in agriculture, installation of insulation of housing to protect from heat, etc. These different types of investments will have different impacts on emissions. For instance, insulation reduces energy use, and thus carbon emissions, but changes in agricultural practices have an ambiguous impact. However, the total impact of adaptation on GHG emissions is unlikely to be marginal, considering the magnitude of forecasted investment levels. For public authorities only, the World Bank (2010) has estimated that the global cost of necessary adaptations to climate change could be between $ 70 billion and $ 100 billion between 2010 and 2050.

In spite of this, adaptation and mitigation are two topics that are usually independent in political practice: mitigation policies focus on the decarbonisation of industry, agriculture and services, whereas adaptation measures consist in planning and carrying out necessary investments (e.g. dykes). A better understanding of the impact of adaptation on GHG emissions is necessary to encourage the implementation of adaptation strategies that do not put more pressure on climate mitigation.

As adaptation strategies differ across sectors, sector-specific analyses, and often region- or country-specific analyses are necessary. In this paper, we focus on the US residential sector and analyse the impact of temperature shocks on housing investment behaviour and on residential energy consumption and carbon emissions. To so do, we use micro-data from 14 biannual and national waves of the American Housing Survey (AHS, 1985-2011), which includes detailed information on the improvements performed in a large panel of US homes. The data from the AHS has been matched with climate data from the National Oceanographic Atmospheric Association Data Center gathered for 159 localities in the US. We use three climate variables: the count of heating degree days, of cooling degree days and the number of days with precipitations higher than 0.5 inches to control for precipitations and humidity. Energy price data at State level are collected from the US Energy Information Administration. The time period covered by our data is extensive, which allows us to capture the impact of changes in climate on the decisions of specific households over time.

We use the results of our econometric models of home improvement and energy consumption to simulate the impact of a 1 Fahrenheit degree increase of US average inland temperature on residential gas and electricity consumption. Our econometric and simulation show that households will use air conditioning more intensively, which will drive electricity consumption upwards (+3.5% for a 1 Fahrenheit degree increase). However, the increase in electricity consumption could be compensated for by a reduction in gas demand (-5.1% for a 1 Fahrenheit degree increase) due to a reduced use of gas heaters in winter. All in all, we find that energy demand decreases by 1.9% in the long run with a 1 Fahrenheit degree increase.

The impact of the cut in energy consumption on emissions depends on the energy mix of power generation. Currently, electricity produces more GHG emissions than gas in the US. Therefore, the shift from gas demand towards electricity, as predicted by our model, would lead to a slight increase (+0.8% with a 1 Fahrenheit degree increase in our simulation) of GHG emissions imputable to residential energy demand if today's facilities were used to produce electricity in the distant future. Our results therefore gives a new reason for US policy-makers to insist on the decarbonisation of electricity generation, considering that household level adaptation is likely to favour electricity, both for space heating and air-conditioning.

These results are in line with those obtained by Deschênes and Greenstone (2011), Auffhammer and Aroonruengsawat (2011) and Amato *et al.* (2005). Deschênes and Greenstone (2011) estimate that, by the end of this century, residential energy consumption could rise by 11% in the US as a result of climate change. Similarly, Auffhammer and Aroonruengsawat (2011) examine household-level electricity consumption data in California from 2003-2006. Using a very large sample of monthly and geolocalized data, they run a model of short-run response of energy demand to shocks in temperature. In a second stage, they use their model results to run simulations of residential electricity demand under the A2 (high emissions) and B1 (low emissions) climate scenarios of the Intergovernmental Panel on Climate Change (IPCC, 2000).[40] Assuming no change in Californian population and electricity prices, these authors find that, under the A2 scenario, Californian residential

[40] The B1 scenario is a "sustainability" scenario with relatively low GHG emissions. IPCC (2001) predicts that the B1 scenario should lead to a 1.9°C temperature increase between 2000 and 2100. On the other hand, under the A2 scenario, GHG emissions are substantially larger and IPCC (2001) predicts a 3.6°C temperature change over the 21st century.

electricity consumption will rise by 48% in 2080-2099 compared to 1980-2000 levels. In the B1 scenario, the rise in residential electricity consumption is 18%. If climate change is not properly mitigated, the results of Auffhammer and Aroonruengsawat (2011) show that electricity consumption could increase substantially in California. Likewise, Amato *et al.* (2005) analyse the impact of temperature shocks on residential electricity consumption, in Massachusetts. They find that residential electricity consumption increases in a series of climate change scenarios as compared with a no-climate change scenario. According to Amato *et al.* (2005), the increases in electricity consumption during summer months should outweigh the decreases in the winter months. However, they forecast that heating oil and gas consumption should decrease in Massachusetts as a result of climate change.

We go deeper into the analysis of the relationship between climate change and residential energy demand in several respects. To our knowledge, this paper is the only one to resort to household level panel data to estimate nationwide residential energy consumption over the past 20 years. Auffhammer and Aroonruengsawat (2011) use household level data but focus on electricity consumption between 2003 and 2006 in California. Their time span is relatively short and their results specific to California. Furthermore, these authors use monthly shifts in temperatures to assess climate change impacts. This is a limitation as the use of variables covering longer time periods is preferable to study climate change, as explained by Deschênes and Greenstone (2011).

Second, we deal with both electricity and gas consumption. Extending the analysis to gas is crucial because it is widely used for space and water heating in the US. Furthermore, one would expect that higher temperatures would reduce gas use in some regions, as in the case of Massachusetts (Amato *et al.*, 2005). Mansur, Mendelsohn and Morrison (2008) analyse US energy demand in a setting in which fuel choice decisions are endogenous. Using a multinomial choice framework, they show that households prefer electricity to other fuels when temperatures are high, in particular because electric heating appliances have lower installation costs and fit more in regions where space heating is not intensive.

A third contribution is that we explicitly consider the mechanisms that make the link between climate change and residential energy consumption. More precisely, we proceed in two steps. First we estimate how temperature shocks modify investments in dwellings. We then assess the impact of the investments made on energy consumption and GHG emissions. This allows us to derive additional findings, in particular that households may invest less in insulation when temperatures get higher, which may put more pressure on energy demand and lead to additional GHG emissions under climate change. Deschênes and Greenstone (2011), Auffhammer and Aroonruengsawat (2011) and Amato *et al.* (2005) do not open the "black box". They directly study the relationship between the climate variables and energy consumption.

The remaining of this paper is structured as follows. In the following section, we develop a home investment model to represent households' home improvement decisions, both the likelihood that investments occur and the intensity of the investments, conditioned on investments taking place. The results of the home investment model feed into a statistical analysis of the sensitivity of energy demand to climate change in the short and the long runs. Section 3 presents the data and section 4 the estimation results. Finally in section 5, we run a simulation to assess the implications of our econometric results.

2. Model

Home improvements

Outside economics, looking at the nature of the building stock and its fitness to climate is not particularly original: there are many historical examples of human settlements that adapted to their climate. In fact, a large share of past adaptations to climate can be found in vernacular architecture, i.e. the architecture that grew out of "the needs of the inhabitants of a place and the constraints of site and climate" (Oktay, 2002). For instance, dwellings are usually oriented to the south and placed below a hill to protect from winds in cold countries.

Within economics, the determinants of home improvements have been studied in a series of empirical papers at least since the 1970s. Apart from a few regional-level examples (e.g. Mendelsohn, 1977; Mayer, 1981; Melchert and Naroff, 1987; or Helms, 2003), the empirical analysis of US home renovation has principally relied on the data from the American Housing Survey (AHS), examined at different time periods and for different geographical areas (Shear, 1983; Reschovsky, 1992; Bogdon, 1996; Montgomery, 1996; Baker and Kaul, 2002; Gyourko and Saiz, 2004; Plaut and Plaut, 2010). However, previous empirical research on home improvements has focused on the socioeconomic characteristics of households and homes that undergo renovation. To the best of our knowledge, no research on US home improvements has ever looked at the impact of climate change on household decisions.

Previously, scholars using the AHS data on home improvements have principally relied on probit and tobit models. In fact, home improvements can be interpreted as a left-censored variable because investments are only observed with a positive value. The probit and tobit models are run on a cross-section of residential units and the data from the previous years is used to construct independent variables. Actually, Helms (2003) provides a very simple theoretical model to link household utility and household capital investment, which finally takes the form of a latent variable that can be estimated with a tobit model.

Even though these types of econometric models appear attractive at first sight, they proved to be insufficient to understand renovation efforts. For example, the predictive power of the models of Helms (2003) is very low. Additionally, cross-sectional probit and tobit models may be biased if the independent variables are correlated with the unobservables. Furthermore, tobit models tend to overlook the “lumpy” nature of the investments in home improvements: long periods with no or low investments are usually preceded by more active investment periods.

Various reasons can make home improvements lumpy. In particular, it is unlikely that households will perform similar investments twice over a short time period, because the utility of making an investment depends on the state of decay of the part of the home that is renovated or improved. Additionally, households may prefer to make all the necessary improvements at one point in time, and not to delay them over a longer time period because of the hidden fixed costs associated with home improvements. For example, home improvements may limit the possibility to live in a house while it is being renovated.

This is why the econometric model below tries to consider the lumpy nature of investments in home improvements by referring to a framework developed by the investment literature. Furthermore we use the longest panel available with the AHS and cover the entire US, from 1985 to 2011 and exploit the panel nature of the data by using fixed effects. The long time span also allows us to look both at the short run and the long run impacts of climate change on home improvements.

An empirical application of the (S,s) framework

In the investment literature, it is well known that capital investments by industries are lumpy (e.g. Doms and Dunne, 1998). Dixit and Pyndick (1994) provide the theoretical foundations: in a context in which the optimal level of firm output is stochastic and the decision to invest is costly, firms are better off investing once and for all in new production capacities when the gap between the current and the optimal level of output is sufficiently high to motivate new investments. Likewise, when the level of optimal output reaches a bottom threshold, much lower than the current level of output, disinvestment is the optimal decision. Within an upper bound and a lower bound, the difference between the current and the optimal level of output is too small to motivate an investment or a disinvestment. In this case, the cost of adjustment is higher than the expected utility derived from it.

A family of investment models with adjustment costs is constituted by the (S, s) models, the two "s" corresponding to the upper and the lower bounds of inaction. This "range for inaction" makes any analysis of investment decisions at the micro-level relatively complex: the investment decisions are dependent on past investments and appear in a lumpy fashion, which makes any single investment difficult to predict.

This complexity is well represented by the (S, s) setting of Caballero and Engel (1999). Their model, developed for firm decisions, assumes that the profitability of investing evolves stochastically and entails random adjustment costs proportional to the amounts that have already been invested.

Making the analogy with home improvements is straightforward: shocks on the utility for specific housing services and house depreciation can lead to disequilibria between the level of housing services provided by a house and the level desired by homeowners. On the other hand, home improvements usually affect the possibility of using one's house during the renovation works. Consequently, changes to the current level of stock are likely to entail adjustment costs proportional to the total amounts already invested in housing, but these adjustment costs (if investments are undertaken) may change from one year to the other for reasons unobserved by the econometrician.

Based on Caballero and Engel (1999), we denote the utility U of household i at time t as:

$$U\left(K_{i,t}, \theta_{i,t}\right) = {K_{i,t}}^{\beta} \theta_{i,t} - (r+\delta) K_{i,t}$$

Where $K_{i,t}$ represents the total amount of invested capital in housing by household i at time t, $\theta_{i,t}$ is a stochastic parameter that follows a random walk, r and δ are the discount and the depreciation rates and β is a parameter that is less to one. In the absence of any adjustment cost, the frictionless stock of capital invested in housing, $K_{i,t}^{*}$, would be achieved by the household after maximizing firm utility with respect to K so that:

$$\theta_{i,t} = \frac{r+\delta}{\beta} {K_{i,t}^{*}}^{1-\beta}$$

However, like Caballero and Engel (1999), we consider that households undergo an adjustment cost proportional to the housing services that are foregone when home improvements are made:

$$C(K_{i,t},\theta_{i,t}) = \omega_{i,t}(\pi(K_{i,t},\theta_{i,t}) + (r+\delta)K_{i,t}) = \omega K_{i,t}^{\beta}\theta_{i,t}$$

Where $\omega_{i,t}$ corresponds to the adjustment cost factor. This parameter is stochastic, changes at each time period and follows the distribution function G(.). With adjustment costs, the utility function of the household can be rewritten as a function of the frictionless stock of embedded capital in housing:

$$\pi(K_{i,t}^{*}, z_{i,t}) = \frac{r+\delta}{\beta}K_{i,t}^{*}(e^{\beta z_{i,t}} - e^{z_{i,t}})$$

With:

$$z_{i,t} \equiv \ln\left(\frac{K_{i,t}}{K_{i,t}^{*}}\right)$$

The decision of adjusting or not adjusting becomes dynamic and is computable according to the value function of adjusting capital at time t for a given level of pre-adjustment disequilibrium $z_{i,t}$, frictionless capital stock $K_{i,t}^{*}$ and adjustment cost $\omega_{i,t}$. If we denote $V(z_{i,t}, K_{i,t}^{*}, \omega_{i,t})$ the household's bellman value function, with $V(z_{i,t}, K_{i,t}^{*})$ its realization with no adjustment and $V(c_{i,t}, K_{i,t}^{*})$ its value if the firm adjusts, we can write:

$$V(z_{i,t}, K_{i,t}^{*}, \omega_{i,t}) = \max\left\{V(z_{i,t}, K_{i,t}^{*}), V(c_{i,t}, K_{i,t}^{*}) - \omega_{i,t}\frac{r+\delta}{\beta}K_{i,t}^{*}e^{\beta z_{i,t}}\right\}$$

Here, $c_{i,t}$ is the optimally determined return point after investment: it corresponds to the desired level of capital if the investment/disinvestment decision is made. Similarly, we can define $x_{i,t} \equiv z_{i,t} - c_{i,t}$ as household's imbalance with respect to its target point. Caballero and Engel (1999) show that the solution to this setting can be derived from the policy $\Omega(z_{i,t})$, defined as the largest adjustment cost factor $\omega_{i,t}$ for which an agent would still adjust[41], so that the adjustment hazard Λ according to imbalance $x_{i,t}$ is given by the policy $\Omega(.)$ and the cumulative distribution function G(.) of the adjustment factor $\omega_{i,t}$:

[41] The value of $\Omega(z)$is such that the following equation holds: $V(c, K^{*}) - \Omega(z)\frac{r+\delta}{\beta}K^{*}e^{\beta z} = V(z, K^{*})$

$$\Lambda(x_{i,t}) = G\left(\Omega(x_{i,t} + c_{i,t})\right) \quad (4.1)$$

Furthermore, and by definition, the amount I invested by households once they have decided to invest corresponds to the difference in capital necessary to reach the target point c from current imbalance point x:

$$I(x_{i,t}) = (e^{c_{i,t}} - e^{z_{i,t}})K_{i,t}^{*} = (e^{-x_{i,t}} - 1)e^{z_{i,t}}K_{i,t}^{*} = (e^{-x_{i,t}} - 1)K(x_{i,t}) \quad (4.2)$$

Econometric specification

We make a sequential interpretation of the model of Caballero and Engel (1999). In our reduced-form setting, consumers first decide whether they invest or not and then opt for an amount proportional to their capital imbalance. Importantly though, equation (4.1) and (4.2) suggest that the probability of investing and the amounts that are invested depend on the same latent variable $x_{i,t}$. In our setting, we use a set of independent variables and fixed effects to proxy $x_{i,t}$.

We estimate $\Lambda_{i,t}$ in a first stage. We denote $D_{i,t}$ the decision of making an investment, such that $D_{i,t} = 1$ if an investment is performed by household i at time t, or zero otherwise. As we observe $D_{i,t}$, we can implement a fixed-effect logit model. Thus, we assume that there is a latent variable $D_{i,t}^{*}$ such that:

$$D_{i,t}^{*} = Z_{i,t}'B + \sum_{f} P_{f,t}'\tau_f + \sigma(1-\delta)K_{i,t-1} + u_i + \varepsilon_{i;t}$$

and:

$$D_{i,t} = \begin{cases} 1 \; if \; D_{i,t}^{*} > 0 \\ 0 \; otherwise \end{cases}$$

Above, $Z_{i,t}$ is a vector of independent variables including climate variables, B a vector of parameters, u_i an individual-specific fixed effect and $\varepsilon_{i;t}$ an error term following an extreme value distribution. Moreover, $P_{f,t}$ is the price of fuel f and τ_f a parameter associated with fuel f (e.g. gas or electricity). Furthermore, we expect that the decision D depends on the total amounts of investments that have already been capitalized in the house, i.e. $(1-\delta)K_{i,t-1}$ where δ is the depreciation rate. Finally, σ is a parameter such that $\sigma < 0$: the more improvements that have been performed previously, the less a household will be prone to perform additional home improvements.

The estimation of such a model allows recovering the probability that individual i decides to make an investment. We can apply the formula of the logit model to recover the probabilities of investing, assuming that the fixed effect is equal to zero[42]:

$$\Lambda_{i,t} = \frac{\exp\left(Z'_{i,t}B + \sum_f P'_{f,t}\tau_f + \sigma(1-\delta)K_{i,t-1}\right)}{1 + \exp\left(Z'_{i,t}B + \sum_f P'_{f,t}\tau_f + \sigma(1-\delta)K_{i,t-1}\right)} \quad (4.3)$$

In a second stage, we estimate $I_{i,t}$ with a fixed effect linear regression model such that:

$$I_{i,t} = X'_{i,t}A + \sum_f P'_{f,t}S_f + \rho(1-\delta)K_{i,t-1} + \mu_i + \epsilon_{i,t} \;\; if \; I_{i,t} > 0$$

In the equation above, $X_{i,t}$ is a set of independent variables, A is a vector of parameters, S_f a parameter associated with fuel f, ρ a parameter capturing the influence of past investments on new ones, μ_i is a fixed effect and $\epsilon_{i,t}$ an error component.

Note that we estimate $\Lambda_{i,t}$ and $I_{i,t}$ independently. The limitation of doing so is that there could be a selection bias on $I_{i,t}$ if time-varying unobservables affect the choice of investing or not (i.e. $\Lambda_{i,t}$). However, we reduce this risk by controlling for the main drivers affecting decisions to invest. The first one is the current state of the house, which is captured by $K_{i,t}$, and the second one is household specific tendency to make home improvements, which is to a very large extent controlled for thanks to the use of fixed effects at household level: both the time constant features of housing units and households are controlled for in our setting. Additionally, our base specification controls for income shocks and changes in the number of family members within a household.

Accounting for different types of home improvements

The estimation process above can be applied even when we consider that housing services do not constitute a homogeneous good. If we consider that there are H types of housing services and therefore H types of potential home improvements, we can write as many systems of equations ($\Lambda_{i,h,t}; I_{i,h,t}$) as there are types of housing services. In this case though, the investments performed in type h become dependent on the investments performed in any other type j. This is why we consider that all the $K_{j,i,t-1}$ affect $D^*_{i,h,t}$:

[42] It is not possible to recover the fixed effects of a fixed effect logit model once it has been estimated.

$$D_{i,h,t}^{*} = Z_{i,h,t}'B_h + \sum_f P_{f,t}'\tau_{f,h} + \sum_{j=1}^{H} \sigma_{j,h}(1-\delta)K_{i,j,t-1} + u_{i,h} + \varepsilon_{i,h,t}$$

The amounts to be invested in h depend on the amounts that have been capitalized in all the other types j and in h previous to the investment that is considered. Because the $K_{i,j,t-1}$ are good predictors of $\Lambda_{i,j,t}$ and $I_{i,j,t}$, they allow controlling for the likeliness that investments in other categories occur simultaneously to $I_{i,h,t}$. Furthermore, they are also good indicators about consumers' expectations regarding future home improvements, i.e. the fact that a household can forecast that, within a few years, he/she will have to perform works in his home.[43]

Likewise, we consider that the amounts invested in one category at time t depends on the amounts that have been capitalized in other categories of housing services:

$$I_{i,h,t} = X_{i,h,t}'A_h + \sum_f P_{f,t}'S_{f,h} + \sum_{j=1}^{H} \rho_{j,h}(1-\delta)K_{i,j,t-1} + \mu_{i,h} + \epsilon_{i,h,t}$$

Accounting for previous adaptations of housing services

Since we are interested in energy-related adaptations, present heating degree days and cooling degree days are the most appropriate variables to account for the impact of contemporaneous shifts in temperatures on home improvements. However, past temperatures may also have an impact on the home improvements that are performed at a given year, because they may be correlated with previous adaptation decisions (either to a hotter or a colder weather).

We have tested for the impact of past temperatures on home improvements using the average amount of heating and cooling degree days for the past ten years as an independent variables (i.e. in the vectors $Z_{i,h,t}$ and $X_{i,h,t}$ explaining $D_{i,h,t}^{*}$ and $I_{i,h,t}$). Furthermore, we have tested for the inclusion of interaction variables between the amount of capital dedicated to specific housing services and the past 10-year average amount of both heating and cooling degree days in alternative specifications. These variables would control for previous adaptation of the housing stock to the past climate, which may in return

[43] Note that including the values of $I_{i,j,t}$ as independent variables to explain $D_{i,h,t}$ is not only difficult because these variables would be endogenous, but also because they are censored: we do not always observe at least one investment in all H categories.

explain investment levels at time t. We are reporting a few examples of these tests in Appendix C1.

In our base specifications for $D^{*}_{i,h,t}$ and $I_{i,h,t}$, the interaction variables that proved to be statistically significant have been included as additional independent variables.[44] These variables are different from one equation to the other (i.e. for one type of housing services to the other), which is normal as one interaction may be relevant for one type of housing services (e.g. air-conditioning) and not for the other (e.g. insulation).

Model of residential energy consumption

The model of home improvements presented previously allows capturing household decisions to invest in their homes. This model therefore allows us to assess in which proportions temperature variations could trigger new home improvements. However, the model of home improvements does not say anything about the impact of the adoption of specific adaptations on GHG emissions. To look at this aspect, we model the impact of home improvements on residential energy consumption. We then compute GHG emissions based on our estimates for residential energy consumption.[45]

As already explained, there are two main sources f of energy consumed by US households: electricity (e) and gas (g). We estimate separately the demand for both energy sources using a similar framework. More precisely, we use a linear econometric equation where the dependent variable is the annual energy consumption of fuel f by household i at time t, denoted $q_{i,f,t}$. Like Auffhammer and Aroonruengsawat (2011), we consider that the dependent variable varies with temperature, energy prices and a series of household- and unit-specific features:

$$q_{i,f,t} = M'_{i,t}\phi_{M,f} + \psi_{i,f} + \tau_{t,f} + \varsigma_{i,f,t}$$

$M_{i,t}$ is a vector of independent variables, which includes heating degree days, cooling degree days, days with precipitations, the prices of electricity and gas ($P_{f,t}$ with $f \in \{e, g\}$), and income. $\psi_{i,f}$ is a household-specific fixed effect capturing household-level specificities,

[44] Because we have two variables reflecting past temperatures (heating and cooling degree days), we have pairs of interaction variables between a specific kind of housing services and the past climate. We have tested for the statistical significance of these pairs and have included them in the base specification as soon as one of the variables within a pair proved to be statistically significant.

[45] We therefore disregard the GHG emissions generated by renovation works *per se* and only consider the emissions derived from a change in residential energy consumption.

$\tau_{t,f}$ a time dummy and $\varsigma_{i,f,t}$ is an error term. $\phi_{M,f}$ is a vector of parameters to be estimated.

Moreover, the originality of our approach is that we introduce the expected amount of capital in the housing units into the model as an explanatory variable of energy use. This expected amount of capital, noted $\widehat{K}_{i,j,t}$, corresponds to the previously accumulated capital plus the expected amount of investment made at time t:

$$q_{i,f,t} = \sum_{h=1}^{H} \phi_{h,f}\widehat{K}_{i,h,t} + M'_{i,t}\phi_{M,f} + \psi_{i,f} + \tau_{t,f} + \varsigma_{i,f,t} \tag{4.4}$$

With:

$$\widehat{K}_{i,h,t} = (1-\delta)K_{i,h,t-1} + \hat{I}_{i,h,t}\hat{\Lambda}_{i,h,t}$$

$\phi_{h,f}$ is the vector of parameters that provides information on the impact of home improvements on residential energy consumption, and $\hat{I}_{i,h,t}$ and $\hat{\Lambda}_{i,h,t}$ are the predicted values of $I_{i,h,t}$ and $\Lambda_{i,h,t}$ as estimated with our home improvement model. These predicted values exclude fixed effects, which are assumed to be zero. This is because they cannot be recovered for $\hat{\Lambda}_{i,h,t}$ and this allows enlarging the sample of predictions for $\hat{I}_{i,h,t}$. This could create a bias in the estimation of $\phi_{h,e}$, which we considerably limit as we are estimating $\phi_{h,f}$ not only on $\hat{I}_{i,h,t}\hat{\Lambda}_{i,h,t}$, but on $\widehat{K}_{i,h,t}$ which includes $K_{i,h,t-1}$ and therefore the past realizations of $I_{i,h,t}$.

Energy price endogeneity

Because residential energy prices and consumption levels are simultaneously determined at equilibrium, energy prices are endogenous variables in equation (4.4). We apply a two-stage least square (2SLS) setting to control for electricity and gas price endogeneity.

We construct four instruments based on the average price of gas and electricity in the industrial sector, both within the State in which household i lives and in neighbouring States. These instruments are available at State level and for each year.

Average industrial prices are likely to be correlated to residential prices but should have no impact on residential electricity demand. Likewise, the price of energy in neighbouring States will be correlated with the price of energy in the State in which household i lives. However, changes in the price of energy in neighbouring States should have no impact on the demand for energy of household i. However, simultaneous demand shocks affecting both the industrial and residential sectors (for example a shock on industrial activity affecting household income and therefore residential demand for energy) could lead these instruments to be invalid. To control for this eventuality, we use the 2-year lagged values of industrial prices instead of their contemporaneous values, both within the State and in neighbouring States. Additionally, we apply standard identification tests to control for the statistical validity of our instruments.

Another issue is that the predicted values for the expected amounts of home improvements performed by each household i at time t are also endogenous in equation (4.4) because they are expressed as a function of energy prices. In fact, $\hat{\Lambda}_{i,h,t}$ and $\hat{I}_{i,h,t}$ depend on the price of electricity and gas, and therefore so does $\widehat{K}_{i,j,t}$.

To avoid requiring as many additional endogenous variables as types of housing services, we control for the endogeneity of energy prices with respect to energy consumption since the start, when running the home improvement model.

Therefore, the equations of the home improvement model are not run with the real values for electricity and gas prices, but with predicted values to guarantee, at a later stage, that the $\widehat{K}_{i,h,t}$ are exogenous with respect to electricity and gas consumption. More precisely, before each estimation of $\Lambda_{i,h,t}$ or $I_{i,h,t}$, we run two linear fixed effect models to make predictions for electricity and gas prices. The linear models include the same explanatory variables as for the estimation of $\Lambda_{i,h,t}$ or $I_{i,h,t}$, plus the energy price instruments described above. Then, we estimate the $\Lambda_{i,h,t}$ and $I_{i,h,t}$ with the predicted values for electricity and gas prices, which allows us to recover estimates of $\Lambda_{i,h,t}$ and $I_{i,h,t}$ that are exogenous with respect to residential electricity and gas consumption. Once we have estimated all the $\hat{\Lambda}_{i,h,t}$ and $\hat{I}_{i,h,t}$, we can compute values for $\widehat{K}_{i,j,t}$ that are exogenous in the energy consumption model.

This technique allows us to consider that only energy prices are endogenous in the energy consumption model, as we previously make sure that all the $\widehat{K}_{i,j,t}$ are exogenous. This methodology presents the advantage of reducing the amount of necessary instruments in the 2SLS regression. However, running a weak identification test after the estimation of the 2SLS model may underestimate the potential IV bias, as the test does not take into account the fact that we have controlled for the endogeneity of the $\widehat{K}_{i,j,t}$ beforehand.

We provide in Appendix C2 an example of the type of regressions that is used to predict residential electricity and gas prices. The example corresponds to regressions that have been run before the estimation of one $\Lambda_{i,h,t}$ relative to a specific type h of housing services.

Heterogeneity of the impact of home improvements on energy consumptions

In equation (4.4), two vectors of parameters would provide relevant information about the relationship between climate and energy: $\phi_{M,f}$, the vector of parameters that, once estimated, describes household response to climate shocks with the available capital stock; and $\phi_{j,f}$ which provides information on the impact of home improvements on residential energy consumption.

However, the capital invested in the various categories of home improvements is unlikely to have a constant marginal impact on energy consumption. In fact, home improvements may entail different energy consumption levels at different temperatures. For example, the impact of a better insulation on energy consumption is likely to depend on how extreme outside temperatures are. Therefore, we complement our base specifications for the models of electricity and gas consumption with interaction parameters between the categories of housing services and heating and cooling degree days.

Likewise, we consider that current energy consumption levels may reflect some adaptation to the past climate and use the past 10-year average amount of heating degree days and cooling degree days to account for this effect. Like for the home improvement model, we have also tested various specifications where we have interacted information on the past climate with the total amount of capital corresponding to each type of housing services. Our base specification includes all the interaction parameters that proved to be statistically significant.

3. Data

This paper relies on three data sources to estimate the model of home improvement and the model of residential energy consumption. Firstly, the American Housing Survey is used to gather data on housing units, home improvements, energy consumptions and households. Moreover, meteorological data has been extracted from the National Oceanic and Atmospheric Administration's (NOAA) Data Center. Finally, energy price data for the study period has been obtained from the State Energy Data System (SEDS) monitored by the U.S. Energy Information Administration (EIA).

American Housing Survey (AHS)

Launched since 1973 under the name of Annual Housing Survey, the American Housing Survey includes two samples of US retail estate: a metropolitan and a national one. The national sample is a nationally representative survey of the housing stock of the United States. However, it underwent a redesign in 1985 and the units of 1985 and after are different from the units surveyed during the previous years.[46]

For this study, we have extracted data on households and housing conditions from the national waves of the AHS since its redesign in 1985. We have therefore gathered longitudinal data from 14 waves of the national AHS, from 1985 to 2011. We are not using all the observations of the AHS from 1985 to 2011 though, firstly because the localization of the housing units is confidential for about half of the sample[47] and also because the information on home improvements has been collected for owner-occupied units only. The sample of geolocalised, owner-occupied units between 1985 and 2011 is composed of 262,872 observations.

In the AHS, the geographical information is displayed at the level of the Metropolitan Statistical Areas (MSAs). A MSA is an area which contains a core urban area of at least 50,000 inhabitants and can consist of one or more counties. The AHS waves between 1985 and 2011 include housing units from 144 MSAs, spread all over the United States.[48]

The AHS includes information on different types of home improvements.[49] For this research, we distinguish three types of housing services, corresponding to three types of home

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[46] The metropolitan sample covers a set of 21 metropolitan areas and each metropolitan area is surveyed once every six years.

[47] Principally, the public use files of the AHS do not provide information on the location of the units that are situated in areas with less than 100,000 inhabitants to ensure that the public use files are entirely anonymous. In the end, about half of the owner-occupied units of the AHS are not geolocalised in the public use files.

[48] In 2013, there was a total of 387 MSAs in the US according to the Census Bureau: http://www.census.gov/population/metro/files/metro_micro_Feb2013.pdf

[49] Before 1997, owners were asked about the amount they had invested in 9 different types of home improvements: roofing; insulation; siding; storm doors and windows; installation of major equipment; changes to the bathroom; changes to the kitchen; home extensions; and any other major improvement costing $ 500 or more. In 1997, the typology was refined but we had to stick to the previous typology to be able to use the entire study sample from 1985. Among the nine types of home improvements that were available to us, we decided to follow in detail the two that were the more obviously related to climate adaptation. For the others, we just decided to aggregate them and analyse them as one type of home improvements by its own. On the other hand, please note that we

improvements. The first category covers the installation of major (energy-consuming) equipment, including principally space heating appliances and air conditioners (either room or central air conditioners). The second category covers all the types of improvements that we expect to be directly or indirectly related to *energy integrity*, including direct works to insulate the home (i.e. addition/replacement of foam, weather stripping and caulking), the addition or replacement of storm doors and windows (double or triple glass), roofing jobs and improvements on siding. We expect that works related to energy integrity reduce energy bills, whereas the installation or replacement of major equipment could either increase energy bills with the installation of new equipment or reduce energy bills if old, energy inefficient appliances are replaced with energy efficient ones. On the other hand, the third category consists in all the other indoor amenities[50] which we have considered as not directly related to energy use: changes to the bathroom; changes to the kitchen; home extensions; and any other major indoor improvement.

For all these types of home improvements, we observe the investments performed by households ($I_{h,i,t}$). We however do not know the value of the stock of capital already embodied in a home before the first investment is performed. We extrapolate this initial amount – and from this the total amounts $K_{h,i,t}$ of a type of housing services capitalized by each household at a specific – from the purchase price or the construction cost of the housing units as registered in the American Housing Survey after a transaction or after construction for new buildings.

Let's note $k_{i,t}$ the amount of capital embodied in a home at time t, net of any observed home improvement $I_{h,i,t}$. For the years in which the housing units are either sold or built, $k_{i,t}$ is known to us. For the years following the sale/construction of the house, we input the value of $k_{i,t}$ by applying a depreciation rate on housing capital:

$$k_{i,t} \approx (1-\delta)^{\tau_i} k_{i,t-\tau_i}$$

τ_i represents the observed date of construction or sale. We take 2% for the value of the depreciation rate of past investments (i.e. $\delta = 2\%$). This value corresponds to the depreciation rate of real estate as estimated by Harding *et al.* (2007) on AHS data.

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cannot control for the home improvements realized outside the home, because the information is not recoded before 1997 and we need to use the entire panel to consider climate change adaptation.

[50] As explained in the previous footnote, we have no information on outdoor improvements for the entire survey period.

Additionally, for the years that precede a sale and for which we have no previous information on the initial capitalized investments net of home improvements, we infer it from the sales price of the home at a later date:

$$k_{i,\tau_i-s} \approx \frac{k_{i,\tau_i}}{(1-\delta)^s}$$

s represents the lag between the observed purchase and the time of interest for the calculation of k. This technique allows us to proxy the amount of capital in a home before home investments are made provided that we observe at least one sale or the construction cost of the unit.

We expect our approximation of $k_{i,t}$ to be representative of the value of all the services delivered by the housing unit net of any observed. We however want to distinguish the initial stock of capital associated with major equipment and the initial stock of capital associated with energy integrity from the rest. To do so, we use the information provided by the National Association of Home Builders (NAHB, 2010) on construction costs. According to the NAHB, 20.3% of the construction cost of a single-family unit is due to the lot price. Furthermore, the NAHB also provides a breakdown of the construction cost of a home according to the part of the unit that is considered. In particular, heating, ventilation and air-conditioning systems represent 4.0% of the construction cost, and appliances 1.6% in average. We therefore proxy the initial stock of capital in major equipment, net of any home improvement after τ_i, by evaluating the share of $k_{i,t}$ that is most likely to have been allocated to major equipment at the time of construction based on NAHB (2010). This leads us to apply the following formula:

$$k_{1,i,t} = k_{i,t} * (1 - 20.3\%) * (4\% + 1.6\%)$$

In the equation above, $k_{1,i,t}$ is the capitalized investments in type 1 (major equipment) at time t for household i, net of any improvement performed to the home after τ_i. We can likewise assess the capitalized investments net of home improvements for insulation, storm doors and windows, and all the other home improvements covered with our data.[51]

[51] According to NAHB (2010), Insulation is 1.5% of construction costs, windows represent 2.8%, exterior doors 0.9%, framing and trusses 15.6%, roof shingles 3.8% and siding 5.8%. To assess the initial capital for all the other homes improvements, we consider that it correspond to the remaining

Once the capitalized investments net of home improvements after τ_i have been calculated for all the three types of homes improvements, we add the value of all the home improvements performed in the house since the last purchase (τ_i) or withdraw the sum of all the home improvements done between time t and the observed future purchase (in τ_i) to proxy the value of capitalized investments in a specific type h of housing services at time t:

$$K_{h,i,t} = \begin{cases} k_{h,i,t} + \sum_{s=\tau_i}^{t} I_{h,i,s}(1-\delta)^{t-s} \ if \ t \geq \tau_i \\ k_{h,i,t} - \sum_{s=t}^{\tau_i} I_{h,i,s}(1-\delta)^{\tau_i - s} \ if \ t < \tau_i \end{cases}$$

To get comparable values of $K_{h,i,t}$ through time, $k_{h,i,t}$ and $I_{h,i,s}$ are deflated. The deflator employed depends on each type h of home improvement. For improvements in *energy integrity* and in all other indoor amenities, we use the "housing" component of the US consumers' price index (CPI) of the Bureau of Labor Statistics. For major equipment, the "durable goods" component of the CPI is used. This allows us to control for the impact of innovation on gradually reducing the cost of major appliances over the period under study.

Moreover, the AHS provides household level information, in particular household total income which we use as a control variable in all the equations. We also have information whether the neighbourhood has access to pipe gas and on the time since the household moved in. The latter allows us to identify the moment when a household left and was replaced by a new one in a given housing unit. We can therefore construct household-specific fixed effects.

Additionally, we also extract information on the energy bills paid by households from the AHS. This allows us to calculate the quantities of energy consumed by each household, which constitutes the dependent variable of the second step of our econometric exercise.[52]

share, excluding outdoor features and fees, i.e. lanscaping and sodding (3.2%), wood decks or patios (0.9%), asphalt driveways (1.4%), building fees (1.9%) and impact fees (1.4%).

[52] To do so, we divide the energy bills for electricity and gas by the average price of these fuels in the State in which the housing unit is located. The price data is taken from the Energy Information Administration and is presented just after the climate data. Recently, Ito (2014) has shown than consumers are more responsive to average prices than to marginal prices. Our choice of using average prices seems therefore reasonable.

Finally, for the households who perform home improvements, we know if they have benefitted a low interest loan or grant from a government program to help pay for making any of the alterations to their home. We use this element as a control variable for the amounts that are invested in home improvements. We therefore partly control for the impact of different policy settings on home improvements.

NOAA Climate Data

The climate data has been extracted from the Climate Data Online (CDO) service of the National Climatic Data Center (NCDC), which is monitored by the National Oceanographic and Atmospheric Administration (NOAA).

We have extracted three measures to proxy climatic conditions: heating degree days, cooling degree days[53], and the annual number of days with precipitations over 0.5 inches. We use heating and cooling degree days instead of average temperature because they provide a much more accurate measure of heating and cooling needs. We are using the total number of days with precipitations above 0.5 inches to control for the impact of precipitations on home improvements. This is because precipitations can be correlated with temperatures and not accounting for changes in precipitation levels could bias our results. Furthermore, precipitations are a good proxy for humidity, which is known to increase the perceived sensation of heat and cold.

Our data corresponds to land-based (*in situ*) historical observations recorded by meteorological stations in the US from 1985 to 2011. We use the information from about 2,200 meteorological stations situated in 159 locations that match the metropolitan statistical areas covered with the AHS data. The records are available for different time spans depending on the opening and closure of the meteorological stations. We have extracted the monthly data and then calculated the yearly averages and sums with the meteorological stations that were active during the entire year. For each metropolitan statistical area, we averaged the values recorded in all the nearby active stations[54] to get variables that could be matched with the AHS data.

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[53] The threshold used by NOAA to distinguish heating degree days from cooling degree days in our data is 65 Fahrenheit degrees.
[54] The nearby stations are identified thanks to the geographical search engine of NOAA's National Climatic Data Center.

Energy Price data from the SEDS

The energy price data is taken from the State Energy Data System administered by the U.S. Energy Information Administration. The data includes information on residential and industrial energy prices for each US State from 1985 to 2011.[55]

We combine the energy price data with the AHS data by matching the metropolitan statistical areas of the AHS with the State-level information of the SEDS. Each time at MSA is situated on more than one State, average price values are obtained by calculating the average energy price corresponding to the different States on which a metropolitan statistical area is overlapping.

Furthermore, we construct instruments for energy prices by using the energy price data from the SEDS. We can easily recover the price of neighbouring States and we also have information on energy prices in the industrial sector.

Summary of statistics

Table 4.1 provides the list of the descriptive statistics from all the three data sources that are used for the model estimation. These statistics are reported for the 31,436 observations that were directly used in the model estimations.

This amount may appear as relatively small as compared with the sample of 262,872 observations of geolocalised, owner-occupied units. The reduction in sample size is principally due to the fact that we only have about 55,000 units for which we have either information on the purchase price or the construction cost, matching with our energy and temperature data. Additionally, some observations have missing information on the variables used in the econometric estimations and we have excluded outliers.[56]

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[55] The prices are provided for coal, natural gas, liquefied petroleum gas, electricity, fuel oil, kerosene and wood in dollars per million btu but we are only using the information on gas and electricity prices, as these two fuels are the ones that are principally used by households.

[56] The 2.5% of units with very high or very low values for heating degree days, cooling degree days, electricity and gas prices has been excluded. This is because there could be differences in the response of the households that live in very hot/very cold regions or in regions in which energy is either very cheap or very expensive (as these households could already be very well equipped or on the contrary underequipped in terms of energy conservation). Furthermore, among the observations that perform an investment in one investment category, we have dropped the 2.5% of observations that invested the highest amounts, considering that the investments performed by these households are likely to be structural and to have occurred anyway. Likewise, our data registers many small

Finally, please note that the observations which have been used to make descriptive statistics are not used in all the equations estimated in our setting. This is because some equations focus on the observations for which one investment is recorded.

amounts of investment in any of the three categories, corresponding to small maintenance efforts. To distinguish these small maintenance works from home improvements, we have considered that the 2.5% cheapest alterations recorded in our data should be disregarded. They enter in the calculation of the total embodied capital in the home but are not used in the fixed effect logit models and the linear models. We have also excluded the 2.5% observations with smallest and the 2.5% observations with largest amounts of capital invested in either major equipment, energy integrity or other indoor amenities as well as the 2.5% observations with very high or very low but non-null levels of either gas or electricity consumption.

Table 4.1: Descriptive statistics of the data used

Variable	Unit	Mean	Std deviation
Capitalized investments in main equipment, $K_{1,i,t}$	$	13,759	9633
Share of households making an investment in main equipment	%	8.1%	-
Expenditure in main equipment for those who perform an investment	$	2,652	2,154
Capitalized investments in energy integrity, $K_{2,i,t}$	$	49,641	33,109
Share of households making an investment in insulation	%	20.8%	-
Expenditure in energy integrity for those who perform an investment	$	3,658	4,022
Capitalized investments in all the other home improvements, $K_{3,i,t}$	$	94,845	62,027
Share of households making an investment in a least one of all the other home improvements	%	34.1%	-
Expenditure in other home improvements for those who perform an investment	$	4,916	6,832
Logarithm of total household income	$	11.04	0.91
Percentage of units with at least one air conditioner	%	87.7%	-
Share of households that have benefitted from a government grant or loan to perform home improvements	%	1.0%	-
Share of housing units connected to pipe gas	%	77.9%	-
Climate variables and energy prices			
Heating Degree Days	#	4,048	2,093
Cooling Degree Days	#	1,548	990
Days with precipitation over 0.5 inches	# of days	24.95	10.58
Past 10-year average amount of heating degree days	#	4,078	2,080
Past 10-year average amount of cooling degree days	#	1,517	956
Residential electricity consumption	MM.btu/year	36.14	20.28
Residential gas consumption	MM.btu/year	63.45	58.14
Residential price of electricity	$/MM.btu	40.05	9.01
Residential price of gas	$/MM.btu	8.23	2.47
Variables used to construct instruments			
2-year lagged industrial price of electricity	$/MM.btu	25.92	7.92
2-year lagged industrial price of gas	$/MM.btu	8.23	2.47

Notes. Source: AHS, CDO and SEDS. Survey years: 1985-2011. Number of observations: 31,436. Comments: all the variables in dollars are expressed in 2011 real dollars. The correction of nominal values has been made using the U.S. Consumer Price Index of the Bureau of Statistics of the U.S. Department of Labour. The entire CPI is used to correct energy prices and household income, whereas only the "housing" component is used for capitalised investments in energy integrity and in other indoor amenities and only the "durables" component is used for capitalised investments in major equipment.

4. Model results

The section below presents the model results. First, they are provided for the home improvement model and then for residential energy consumption. For home improvements, the results are separately displayed for the probability of making an investment and then for the amounts that are invested, for the three types of home improvements considered.

Results of the model of home improvements

Results for the decisions to invest in specific types of home improvements

The regression results on the probability to make a specific type of home improvement are displayed in Table 4.2. However, because interaction parameters have been included in the regressions, it is unclear at first glance whether a higher temperature increases or decreases the probability that a specific type of investment occurs. To provide such a piece of information, we additionally compute and report the marginal effect of a change in one heating degree day, and of a change in one cooling degree day at the mean values of the parameters interacting with our climate variables. We also compute the marginal effect of a permanent increase in temperatures by one Fahrenheit degree for every day in the year. This effect is based on the average number of days below and above 65 Fahrenheit degrees in 2011 in the US.[57]

Our results show that the probability of making a new home improvement depends on the total amounts that have already been capitalized in the category that is considered: the more investments have already been capitalized in one category, the fewer households are likely to invest again in this category. This is consistent with the fact that household will not invest twice in similar home improvements. Furthermore, investments in major equipment and in energy integrity appear as complements. The higher previous investments in one of these categories are, the higher is the probability that an investment is made in the other category.

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[57] The average number of days with mean temperature above (below) 65 Fahrenheit degrees has been obtained from the daily records of all the land-based stations active in 2011. These records were extracted from the NOAA Data Centre. In average in the US, around 69.5% days (30.5% days) had an average temperature below (above) 65 Fahrenheit degrees in 2011. On the other hand, we use 65 Fahrenheit degrees as a threshold because it is the one that NOAA has used to compute the heating degree days and cooling degree days of our data.

For major equipment, we find no statistically significant impact of immediate temperatures to trigger new investments. However, we find that the probability to invest is both proportional to the average number of heating and cooling degree days during the past 10 years and to the size of the house, captured by the total amounts capitalized in other indoor amenities. All in all, the probability of investing in major equipment increases with the total number of heating degree days, such that a permanent, one Fahrenheit degree increase in temperature would reduce, in average, the probability that a household invests in major equipment. Note that this effect, which is statistically significant, includes both investments in air conditioning and in heating at the same time, which plausibly means that the higher frequency in the installation of air conditioners would not compensate for the lower frequency in the installation of heating appliances.

Table 4.2: Fixed effect logit model on the decision to perform investments according to the type of investments

Independent variables	Major Equipment	Energy integrity[$]	All other indoor amenities
Lagged stock of major equipment, $K_{1,i,t-1}$	-2.00E-4** (-1.98)	4.72E-4*** (5.78)	2.65E-4*** (4.04)
Lagged stock in energy integrity[$], $K_{2,i,t-1}$	7.11E-5*** (7.45)	-3.49E-4*** (-8.22)	-5.78E-5* (-1.8)
Lagged stock in other indoor amenities, $K_{3,i,t-1}$	-4.89E-5** (-2.19)	3.59E-6 (1.36)	-4.70E-5*** (-15.58)
Heating degree days, $HT_{i,t}$	1.84E-4 (1.19)	3.25E-4*** (3.14)	9.56E-5 (1.04)
Cooling degree days, $CL_{i,t}$	3.55E-5 (0.13)	2.62E-4 (1.38)	8.45E-5 (0.53)
Interactions with past ten year average amount of heating degree days, $\overline{HT}_{i,t}$			
$\widehat{K}_{1,i,t}$ x $\overline{HT}_{i,t}$	-1.72E-8 (-1.45)	-4.37E-8*** (-4.33)	-2.61E-8*** (-3.21)
$\widehat{K}_{2,i,t}$ x $\overline{HT}_{i,t}$		3.14E-8*** (5.56)	1.04E-8** (2.4)
$\widehat{K}_{3,i,t}$ x $\overline{HT}_{i,t}$	7.30E-9** (2.47)		
Interactions with past ten year average amount of cooling degree days, $\overline{CL}_{i,t}$			
$\widehat{K}_{1,i,t}$ x $\overline{CL}_{i,t}$	-1.67E-7*** (-4.32)	-8.89E-8*** (-3.15)	-6.94E-8*** (-2.98)
$\widehat{K}_{2,i,t}$ x $\overline{CL}_{i,t}$		2.07E-8 (1.57)	1.93E-8* (1.85)
$\widehat{K}_{3,i,t}$ x $\overline{CL}_{i,t}$	1.51E-8** (2.24)		
Number of days with precipitations over	-3.60E-3	2.89E-3	2.54E-3

Independent variables	Major Equipment	Energy integrity$	All other indoor amenities
0.5 inches	(-0.65)	(0.74)	(0.74)
Price of electricity (predicted)	8.17E-2* (1.76)	2.95E-2 (0.96)	-1.40E-3 (-0.05)
Price of gas (predicted)	-1.40E-2 (-0.05)	-1.69E-1 (-0.88)	2.76E-2 (0.17)
Household income	9.99E-2** (2.11)	1.28E-1*** (3.7)	1.17E-1*** (4.08)
Number of people in household	4.56E-2 (1.07)	-1.25E-2 (-0.43)	6.91E-2*** (2.75)
Household fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	8,247	14,119	16,894
Cumulative effect of heating degree days at mean values for $\widehat{K}_{1,i,t}$, $\widehat{K}_{2,i,t}$ and $\widehat{K}_{3,i,t}$.	6.39E-4** (2.33)	1.26E-3*** (6.31)	2.55E-4 (1.59)
Cumulative effect of cooling degree days at mean values for $\widehat{K}_{1,i,t}$, $\widehat{K}_{2,i,t}$ and $\widehat{K}_{3,i,t}$.	-8.31E-4 (-1.26)	5.76E-5 (0.12)	9.60E-5 (0.25)
Expected impact of a one Fahrenheit degree increase	-6.97E-4*** (-3.74)	-8.57E-4*** (-6.11)	-1.48E-4 (-1.31)

Notes. T-statistics in brackets. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively. $: Energy integrity corresponds to insulation, storm doors and windows, roofing and siding. Only the interaction parameters that proved to provide statistically significant results (either in interaction with heating degree days or cooling degree days) have been kept in the base specifications.

For investments in energy integrity, we find that a relatively higher amount of heating degree days is correlated with more investments being made. The probability of investing in this category is also correlated with the past climate. However, the impact of past temperatures on the probability to invest depends on the stock of capital already accumulated either in energy integrity or in major equipment. All in all, we find that heating degree days have a statistically stronger impact than cooling degree days in motivating efforts in energy integrity. In this context, an increase in temperatures by one Fahrenheit degree reduces the frequency of investments in energy integrity.

For other indoor amenities, we find no statistical impact of on-the-year heating and cooling degree days on the probability to invest. However, the past climate seems to alter the probability to invest in other indoor amenities. The impact of the past climate on the probability to invest in other indoor amenities seems to depend on the type of heating and cooling installations in the house, as captured in our model by the total amounts of capital embodied in major equipment and energy integrity. For a representative unit, we find that households tend to invest more in this category with cooler temperatures.

Finally, income has a statistically significant impact on the probability of performing home improvements either in major equipment, energy integrity or in other indoor amenities. Based on our regressions, on-the-year electricity prices may have a positive impact on the installation of major equipment whereas gas prices have no statistically significant impact on the probability to invest in home improvements.

Results for the amounts that are invested

As explained in the model section, a fixed effect linear regression model is run on the amounts invested in each of the three types of home improvements. The results, presented in Table 4.3, complement the findings obtained with the fixed effect logit models.

In particular, we similarly find that the amounts already capitalized in one category are lower when high amounts have already been capitalized in this category. On the other hand, high amounts capitalized in other categories are a good indication that household investments in one specific category may be higher.

Table 4.3: Fixed effect linear regression model on the amounts that are invested according to the type of investments

Independent variables	Major Equipment	Energy integrity$	All other indoor amenities
Lagged stock of major equipment, $K_{1,i,t-1}$	-7.44E-1** (-2.3)	2.75E-1*** (3.35)	6.63E-2 (0.72)
Lagged stock in energy integrity$, $K_{2,i,t-1}$	2.22E-2 (0.85)	-3.98E-1*** (-13.1)	8.73E-2*** (2.79)
Lagged stock in other indoor amenities, $K_{3,i,t-1}$	8.76E-3 (1.09)	2.66E-2** (2.28)	-1.96E-1*** (-8.02)
Heating degree days, $HT_{i,t}$	3.16E-1 (1.37)	-3.78E-1 (-1.05)	1.83E-2 (0.05)
Cooling degree days, $CL_{i,t}$	1.03E+0 (0.94)	-5.93E-1 (-0.86)	6.15E-2 (0.09)
Interactions with past ten year average amount of heating degree days, $\overline{HT}_{i,t}$			
$\widehat{K}_{1,i,t}$ x $\overline{HT}_{i,t}$	7.56E-5** (2.45)		
Interactions with past ten year average amount of cooling degree days, $\overline{CL}_{i,t}$			
$\widehat{K}_{1,i,t}$ x $\overline{CL}_{i,t}$	1.22E-4 (1.06)		
Number of days with precipitations over 0.5 inches	1.20E+1 (0.71)	5.50E+0 (0.36)	-6.33E+0 (-0.37)
Price of electricity (predicted)	-1.73E+2 (-1.04)	-7.38E+1 (-0.52)	-9.57E+1 (-0.78)
Price of gas (predicted)	-3.55E+2	-3.93E+2	-2.77E+1

Independent variables	Major Equipment	Energy integrity[$]	All other indoor amenities
	(-0.22)	(-0.5)	(-0.04)
Household income	-2.07E+1 (-0.16)	4.94E+1 (0.36)	4.98E+2*** (3.2)
Number of people in household	-1.35E+2 (-0.82)	-5.83E+1 (-0.48)	-5.43E+1 (-0.41)
Benefitted from government loan or grant for making home improvements	4.55E+2 (1.08)	5.30E+2 (0.88)	2.73E+3*** (3.62)
Household fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	2,540	6,544	10,715
R^2	0.29	0.18	0.10
Cumulative effect of heating degree days at mean values for $\widehat{K}_{1,i,t}$, $\widehat{K}_{2,i,t}$ and $\widehat{K}_{3,i,t}$.	1.33E+0*** (3.29)	-3.78E-1 (-1.05)	1.83E-2 (0.05)
Cumulative effect of cooling degree days at mean values for $\widehat{K}_{1,i,t}$, $\widehat{K}_{2,i,t}$ and $\widehat{K}_{3,i,t}$.	2.67E+0 (1.05)	-5.93E-1 (-0.86)	6.15E-2 (0.09)
Expected impact of a one Fahrenheit degree increase	-1.13E-1 (-0.16)	8.17E-2 (0.27)	6.06E-3 (0.02)

Notes. The sample includes only observations for which an investment is recorded. Standard errors are clustered on households. T-statistics in brackets. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively. $: Energy integrity corresponds to insulation, storm doors and windows, roofing and siding. Only the interaction parameters that proved to provide statistically significant results (either in interaction with heating degree days or cooling degree days) have been kept in the base specifications.

For major equipment, the amounts invested are generally higher if the past climate has been cold and if households have already capitalised high amounts in major equipment. All in all, heating degree days have a statistically significant impact on the amounts invested. However, the effect of cooling degree days is unclear: the coefficient is stronger than for cooling degree days but not-statistically significant. This is why the impact of a permanent one-degree Fahrenheit increase is unclear and not statistically significant.

For investments in energy integrity and other indoor amenities, we find no clear correlation between temperatures and the amounts that are invested. For other indoor amenities, one of the best predictors of the amounts that are invested is income. We furthermore find a statistically significant impact of government grants or loans on the amounts invested in this category.

Results of the model of residential energy consumption

The predictions of the home improvement model are used as explanatory variables in linear two-stage least square models of energy consumption. At mean values, the impact of additional capital in major equipment is however not statistically significant; this is because the statistically significant interactions with this variable compensate one another. Table 4.4 displays the estimates for both electricity and gas consumption.

We find various statistically significant interactions between temperatures and the capital embedded in any of the three categories of housing services. At first glance though, the marginal impact of a change in capital or a change in temperature is not easy to read because of the many interaction parameters included in the regressions. Like for the home improvement model, we compute marginal impacts at mean values for a change in capital or a change in temperature.[58]

Table 4.4: Fixed effect 2SLS models of residential energy consumption

Independent variables	Electricity	Gas
Stock in major equipment, $\widehat{K}_{1,i,t}$ (predicted)	-7.46E-4* (-1.69)	-3.68E-3*** (-3)
Stock in energy integrity[$], $\widehat{K}_{2,i,t}$ (predicted)	-2.00E-4 (-1.02)	1.44E-3** (2.23)
Stock in other indoor amenities, $\widehat{K}_{3,i,t}$ (predicted)	5.31E-5*** (3.34)	1.99E-5 (0.35)
Heating degree days, $HT_{i,t}$	2.68E-3*** (3.06)	4.07E-3 (1.41)
Cooling degree days, $CL_{i,t}$	3.43E-3** (2.42)	9.16E-3** (2.18)
Past ten-year average amount of heating degree days, $\overline{HT}_{i,t}$	-5.46E-3** (-2.06)	2.90E-2*** (3.05)
Past ten-year average amount of cooling degree days, $\overline{CL}_{i,t}$	-1.30E-3 (-0.37)	4.48E-2*** (3.64)
Interactions with contemporary climate		
$\widetilde{K}_{1,i,t}$ x $HT_{i,t}$	-2.34E-7** (-2.23)	-1.01E-6*** (-3.17)
$\widetilde{K}_{1,i,t}$x $CL_{i,t}$	-1.76E-7 (-0.92)	-1.35E-6** (-2.22)
$\widetilde{K}_{2,i,t}$x $HT_{i,t}$	6.20E-8** (2.07)	2.47E-7** (2.47)
$\widetilde{K}_{2,i,t}$ x $CL_{i,t}$	7.56E-8 (1.43)	2.71E-7 (1.5)
Interactions with past climate		
$\widetilde{K}_{1,i,t}$ x $\overline{HT}_{i,t}$	2.28E-7* (1.91)	1.56E-6*** (4.15)
$\widetilde{K}_{1,i,t}$ x $\overline{CL}_{i,t}$	6.47E-7*** (2.68)	2.36E-6*** (2.98)

[58] At this stage, we do not report the effect of a one-degree Fahrenheit increase because we need to take into account the impact home improvements on energy consumptions. This is done in the last section of this paper.

Independent variables	Electricity	Gas
$\widetilde{K}_{2,i,t}$ x $\overline{HT}_{i,t}$	-2.02E-8 (-0.5)	-4.24E-7*** (-3.1)
$\widetilde{K}_{2,i,t}$ x $\overline{CL}_{i,t}$	-1.31E-7 (-1.51)	-8.08E-7*** (-2.71)
Number of days with precipitations over 0.5 inches	-9.98E-3 (-0.48)	3.43E-3 (0.06)
Price of electricity (instrumented)	-3.84E-1** (-2.36)	-1.13E+0* (-1.72)
Price of gas (instrumented)	2.30E+0** (2.43)	-5.06E+0* (-1.69)
Household income (logarithm)	3.98E-1*** (2.64)	1.20E+0** (2.33)
Number of people in household	2.05E+0*** (12.46)	2.57E+0*** (4.85)
Household fixed effects	Yes	Yes
Year dummies	Yes	Yes
Validity of instruments		
Underidentification test (p-value)	0.00	0.00
Weak identification test (Max. IV relative bias, and Kleibergen-Paap rk Wald F statistic in brackets)	<5% (1529)	<5% (1001)
Over-identification test (p-value)	0.30	0.61
Observations	25,409	18,127
Marginal effects at mean values		
Heating degree days	-7.35E-4 (-0.3)	3.25E-2*** (3.73)
Cooling degree days	6.71E-3** (2.04)	4.22E-2*** (3.5)
Capitalised investments in major equipment	-3.57E-5 (-0.34)	1.15E-4 (0.35)
Capitalised investments in energy integrity	-1.17E-4*** (-2.86)	-7.25E-5 (-0.53)
Capitalised investments in other indoor improvement	5.31E-5*** (3.34)	1.99E-5 (0.35)

Notes. 2SLS regression with fixed effects. Standard errors are clustered on households. For gas, we are only considering households that report a level of residential consumption different from zero. For the two equations, instruments are the 2-year lagged industrial electricity and gas prices, both within the State and in neighbouring States. T-statistics in brackets. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively. $: Energy integrity corresponds to insulation, storm doors and windows, roofing and siding.

At mean values, cooling degree days have a statistically significant impact on electricity consumption at 5%, implying that rising temperatures may raise electricity bills. For gas consumption, the estimated impacts of heating and cooling degree days are both statistically significant. As there are more heating degree days than cooling degree days in a year, the model would predict that a rise in temperature should lead to a decrease in gas consumption.

As regards the impact of the different types of housing services on electricity and gas consumption, some of the results are statistically significant for electricity whereas they are not for gas when aggregated to compute a marginal impact at mean values. In the case of electricity, investments in energy integrity lead to a reduction in electricity bills whereas investments in other amenities increase electricity bills. At mean values, the impact of additional capital in major equipment is however not statistically significant; this is because the statistically significant interactions with this variable compensate one another.

5. Implications of model results for GHG emissions and US residential energy consumption

This section aims to articulate the results of the home improvement model with the results of the energy consumption model and provide a quantitative assessment of the impact of higher temperatures on energy consumption, with particular attention being paid to the impact of household-level adaptation to climate change.

To do so, we run a simulation based on the estimated coefficients of the home improvement model and the energy consumption model. Please note beforehand that the results should not be interpreted as a simulation of the impact of long term climate change on temperatures, as the simulation below does not take into account many factors that will affect energy demand, in particular economic and population growth, or the likely changes in the technologies used for space heating and air-conditioning. This is why our simulation does not aim to provide an estimate of energy demand within 20 or 50 years, but is above all interested in analysing if climate adaptation is a driver of residential energy demand. We want to assess if, based on the model results, we should expect that adaptation of the housing stock increases or reduces energy demand if climate were to evolve.

Our simulation is run for a representative household whose initial capital stock in each type of housing services is equal to the average of our data sample. Likewise, we assume that this representative household consumes an amount of electricity and an amount of gas equal to our data average and is subject to heating and cooling needs corresponding to the mean heating degree days and cooling degree days of our sample. Similarly, his probability to perform an investment in one category and the amount that he would invest are equal to the average predicted probability and predicted amount obtained with our sample.

To assess the impact of climate change on electricity while allowing for capital adjustments in housing services, we construct a baseline scenario in which there is no climate change and then compare it with a climate change scenario. For the baseline scenario, we recurrently compute, from one year to the other, the evolution of the capital stock of the representative household assuming no change in heating or cooling degree days. The change in capital stock is then simply driven by the fact that we have predicted an average amount of investments to be performed each year (equal to the expected probability of investing times the predicted amount that is invested at each time period), which evolution depends on the capital already accumulated in major equipment, energy integrity and other indoor home improvements. From one year to the other, we can therefore define baseline values for the amount of capital embodied in each category of housing services. Additionally, we create baseline electricity and gas consumption values. They correspond to the average electricity and gas consumption of our sample, which are adjusted to take into account the predicted changes in capital likely to occur from one year to the other.

In parallel, we construct a scenario in which temperatures are set to be one Fahrenheit degree higher than in the baseline scenario just after the start of the simulation, at period 1. This leads to a decrease in the number of heating degree days and an increase in the number of cooling degree days, which we have calibrated according to the average number of days above and below 65 Fahrenheit degrees in the US in 2011.[59] We disregard the effect of such a change in temperatures on precipitation levels.

In the climate change scenario, the representative household responds to the temperature shock by increasing immediately his electricity and gas use, and also adapts through home improvements which have persistent effects on energy consumption: the different in temperature modifies the amounts of capital that are invested each year in the three categories of housing services. The changes in invested capital are calibrated based on the probabilities to invest and the predicted amounts that are invested according to the econometric model of home improvements. The simulated values for the accumulated capital in the three types of housing services are reported in Appendix C3 for the baseline scenario and the scenario with higher temperatures.

[59] This is based on NOAA daily records for the US as extracted for the NOAA Data Centre. We consider that there are around 69.5% days below 65 Fahrenheit degrees in the US.

Impacts in terms of energy consumption

Figure 4.6 and Figure 4.7 present the evolution of electricity and gas consumptions as simulated for our representative household. We have considered up to 50 periods in the simulation to be able to capture long run impacts on energy use.[60] In both figures, the grey line corresponds to the scenario without climate change whereas the black line corresponds to the scenario with higher temperatures. The difference between the two lines corresponds to the impact of a one-degree Fahrenheit increase, including both immediate shocks from higher temperatures and capital adjustments. The simulation predicts a progressive shift from gas (-5.1% in the long run) to electricity (+3.5%). Interestingly, this shift from gas to electricity consumption reduces total energy demand by 1.9%, estimated at 101.8 MM.btu[61] for the representative household at the end of the simulation in the baseline scenario, versus 99.9 MM.btu in the climate change scenario.

Since this simulation is based on the coefficients as estimated from the electricity and gas consumption models, it is possible to analyse the contribution of each type of housing services to gas and electricity consumption under the assumption that our estimates correspond the true coefficient values.

To ease the analysis, we group the various coefficients of the regressions into 6 categories of effects. For major equipment and energy integrity, we distinguish *short-run effects*, correlated with present temperatures, from *long-run effects*, correlated with previous temperatures (e.g. due to progressive changes in the composition of installed capital). For the impact of other indoor amenities, we do not distinguish short run from long run impacts as we have not included interaction parameters between this type of housing services and climate variables in the energy consumption models.[62] Finally, we also compute the effect of temperatures (both present and past) on energy consumption that cannot be directly explained by a change in the composition or the amount of embedded capital.

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[60] Please note that the impact of the past climate on energy consumption is progressively taken into account in the first eleven periods since the average number of heating and cooling degree days over the past 10 years steadily adjusts to the permanent increase in temperature (which has started at period 1).

[61] One million British thermal unit is equivalent to around 293 kWh.

[62] These interactions proved not to be statistically significant in alternative test specifications.

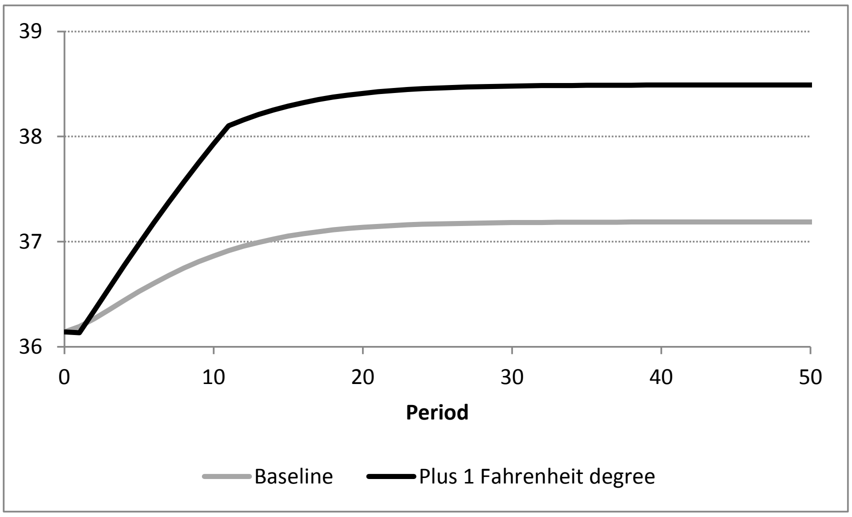

Figure 4.6: Electricity consumption under the baseline and climate change scenarios (million btu for the representative household)

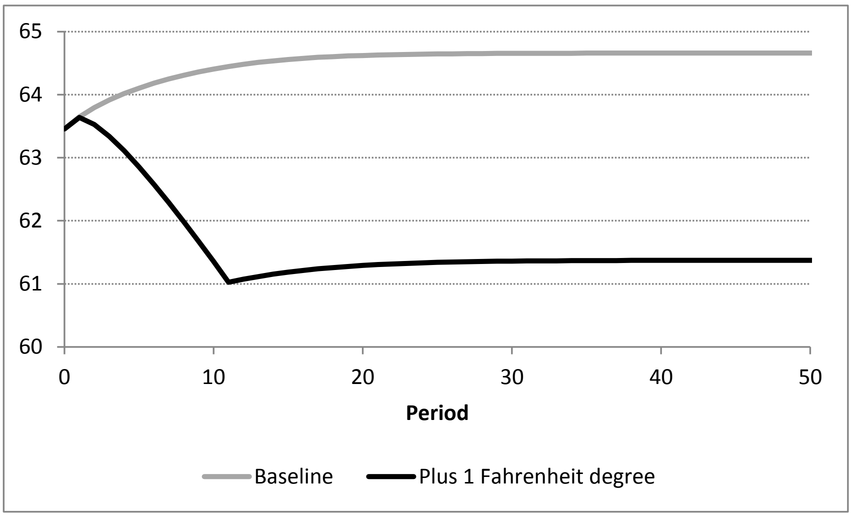

Figure 4.7: Gas consumption under the baseline and climate change scenarios (million btu for the representative household)

Figure 4.8 synthesises the contribution of each type of effect in increasing electricity consumption when temperatures get warmer. In the short run, more electricity is consumed by major equipment, but also more savings are obtained from insulation, which is consistent with the fact that insulation generates more savings under more temperature stress. In the long run though, households seem to adapt the types of major equipment they have at home to their new needs in terms of space heating and air conditioning, which reduces electricity bills in the simulation. On the other hand, because the home improvement model predicts that households reduce their efforts in insulating their homes under warmer temperature, an additional amount of electricity is being consumed in the long run due to a decrease in insulation levels. All in all, we can understand from the graph that this is the more intensive use of already installed installation that could cause an increase in electricity demand.

The contribution of the six categories of effects to residential gas consumption is provided by Figure 4.9. Interestingly, temperatures reduce gas consumption, but this effect is smaller if the amount of major equipment is relatively important. This is consistent with the fact that, in the short run, households may not fully switch off gas heaters. However, in well insulated homes, the increase in temperature leads to more savings being made on gas consumption. In the long run, we find the expected effect that consumers may adapt their heating devices to new climatic conditions and depart from using large gas heaters, maybe in favour of electric heaters. In the end, the decrease in gas consumption in the simulation is concomitant with the changes operated on major equipment: adaptation of the equipment installed therefore seems to be the main driver in the reduction of gas demand. However and as for electricity, the reduced efforts in insulation may translate into extra amounts of gas being consumed in the winter in the long run, all things being equal. This result suggests that there is a need to increase public awareness on the benefits of insulation, even under warmer temperatures.

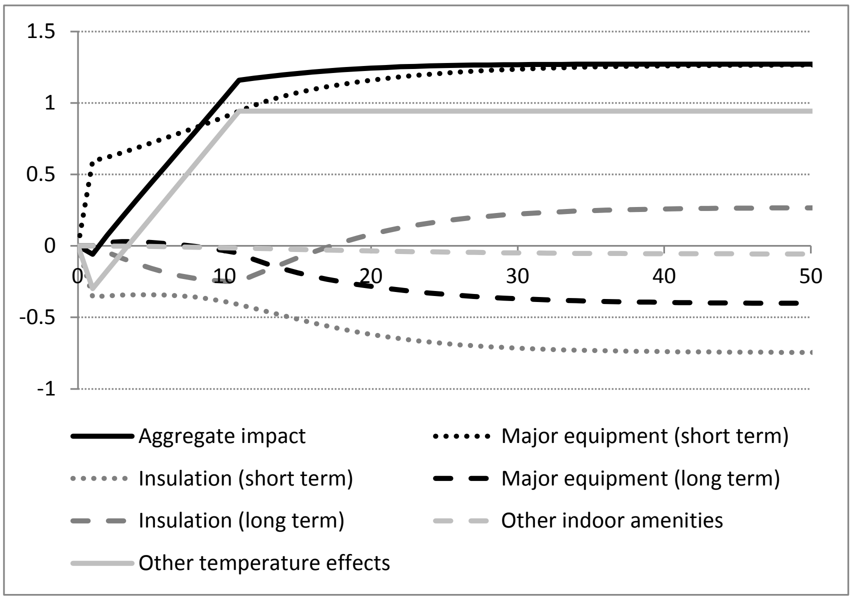

Figure 4.8: Relative contribution of various factors to a change in electricity consumption associated with a permanent increase in temperatures by 1 Fahrenheit degree (million btu for the representative household)

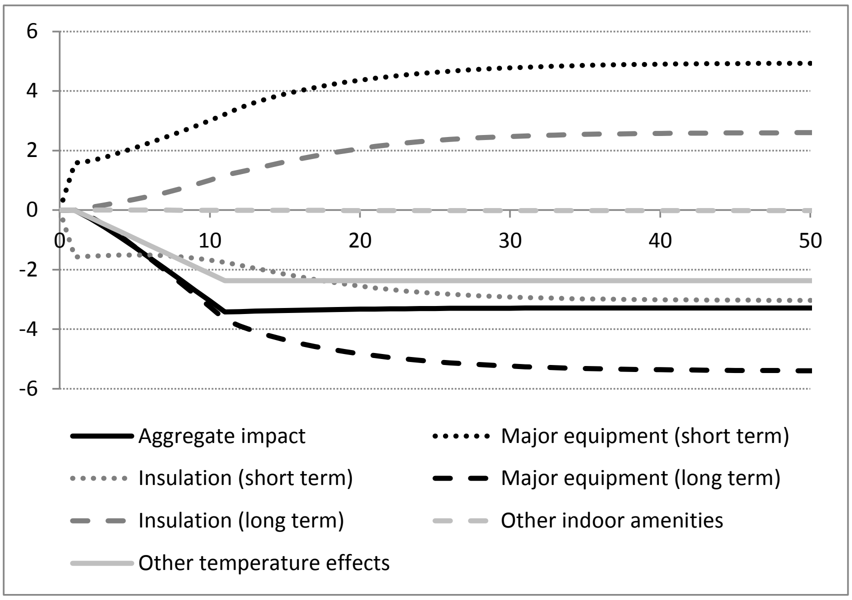

Figure 4.9: Relative contribution of various factors to a change in gas consumption associated with a permanent increase in temperatures by 1 Fahrenheit degree (million btu for the representative household)

Impacts in terms of GHG emissions

We convert the predicted changes in energy use in GHG emissions to analyse the impact of the adaptation of energy demand on climate change mitigation. We use the emissions factor of the Greenhouse Gas Equivalencies Calculator of EPA: one million btu of electricity corresponds to 202.16 kg of CO_2 equivalent and one million btu of natural gas to 53.02 kg CO_2 equivalent.[63] At using these emissions factors, we convert energy consumption from electricity and gas in GHG emissions while making the strong assumption of no change in the energy mix of electricity generation in the long term.

The results of this calculation pinpoint that, if electricity goes on being generated with current energy mix, the GHG emissions produced from residential energy consumption could increase (+0.8% at the ending period of our simulation) as a result of temperature changes, in spite of a total residential energy demand reduction by 1.9%. On the contrary, would we assume twice fewer emissions from electricity generation, the impact of residential adaptation to climate change could lead to a net reduction of GHG emissions by 0.6% in the long run.

[63] http://www.epa.gov/cleanenergy/energy-resources/calculator.html#results. Website consulted in March 2014.

These values are relatively small in magnitude since they have been obtained from an increase in land-based temperatures by 1 Fahrenheit degree. By the end of the century, the RCP6.0 scenario of IPCC (2013), corresponding to a medium-high level of GHG emissions rejected into the atmosphere, predicts an inland temperature increases by around 3 Celsius degrees, i.e. 5.4 Fahrenheit degrees. Calibrated to an increase by 3 Celsius degrees, we find that the shift from gas to electricity could result in an increase of GHG emissions by 4.4% if electricity would still be produced with carbon-intensive methods by the end of the century, or to a decrease in GHG emissions by 3.2% with twice less carbon intensive an electricity.

Therefore, if electricity generation was decarbonised, then the shift of residential demand from gas to electricity may not generate additional GHG emissions but savings: long term adaptation to climate change in the residential sector could have a positive impact in terms of climate mitigation.

6. Conclusion

This research has developed a two-stage econometric model to analyse residential electricity and gas consumption. In the first stage, we have analysed the responsiveness of residential renovation efforts to climatic change. The results of our first stage have then been used in the second stage to predict how residential electricity and gas demand could evolve under climate change.

This research finds that total energy demand could decrease in the US as a result of climate change, with an estimated decrease by 1.9% for each additional Fahrenheit degree. However, residential energy demand would shift from gas to electricity, which consumption has been simulated to rise by 3.5% for each additional Fahrenheit degree. From the perspective of climate mitigation and due to the high carbon content of US electricity, the reduction in total energy demand would not be enough to offset the additional GHG emissions created by a shift in residential demand from gas to electricity. Our research therefore pinpoints that, as electricity is likely to be more and more often used as a principal source of energy in residential units, particular attention should be paid by policy-makers to reduce the carbon footprint of electricity.

Some of the results of this research have already been found by previous scholars, in particular Deschênes and Greenstone (2011) and Auffhammer and Aroonruengsawat (2011) regarding the relationship between temperature shocks and electricity consumption. Our contribution is to provide a statistical analysis of the reasons behind the likely increase in electricity consumption under climate change. Above all, we find that this increase should be compensated by a decrease in gas consumption, and that the principal driver of all these changes would be both a modification in the composition of the equipment installed in dwellings and in the intensity in use of already installed appliances.

In particular, our model predicts that the increase in electricity consumption will be due to a more frequent use of already installed appliances. Conversely to Sailor and Pavlova (2003), we do not find that the diffusion of air-conditioning (i.e. the installation of new air-conditioners), will be the main driver of future electricity demand. However, our model predicts that households are likely to reduce insulation efforts, with a substantial impact on both electricity and gas consumptions.

Precautions should be however taken at analysing our model results, as we have assumed no economic growth or demographic evolution. Furthermore, we have assumed no change in the technologies available to households for space heating and air-conditioning, in terms of energy efficiency, but also in terms of fuel choice for space heating or air-conditioning: for example our results are conditional on gas not being used more often for air-conditioning.

Additionally, note that the US housing stock is relatively specific to the extent that gas consumption is high and air-conditioning is already present in many US homes: 86% of households in our sample declared having at least one air-conditioner at home, whereas 77% live in neighbourhoods connected to pipe gas. Thus, there is clearly a need in conducting similar studies on the relationship between climate change and energy demand in other countries, in particular developing countries that face high constraints in terms of energy security.

General conclusions

In the first part of this PhD dissertation, we have highlighted that consumers do take into account energy costs to a large extent before purchasing domestic appliances, surely thanks to the implementation of the EU energy label and growing environmental awareness among consumers. However, various margins of progress exist to increase the energy efficiency of durable goods.

Chapter 1 confirms that market failures are likely to reduce the impact of electricity prices on the energy consumption of sold appliances. Our econometric estimation shows that consumers may still underestimate energy costs by 35% on the UK cold appliance market despite the implementation of the EU energy label. Energy efficiency has become a salient product feature that can allow substantial mark-ups in a cold appliance market that is imperfectly competitive. As such, imperfect competition might become a thwart to the diffusion of energy efficient appliances if the mark-ups of energy efficient products are so high that consumers are encouraged to keep purchasing energy inefficient products. In our simulation, we find that the impact of imperfect competition on energy demand offset short run demand adjustments. This is only in the long run that electricity price increases lead to energy savings as manufacturers adapt by launching new, more energy efficient products.

Chapter 2 points up that careful attention should be paid to the regulatory failures that can affect the implementation of energy efficiency policies. In particular, the EU energy label will be fully effective only if the promised energy savings correspond to the energy consumed by the appliances that are purchased. On the other hand, compliance with regulation for retailers and manufacturers is not effortless and policy-makers must be aware of the difficulties associated with compliance. In this direction, the simplification brought to the energy label with the replacement of texts by pictograms has eased the work of suppliers, no longer forced to adapt the label to the country of sale. On the other hand, the unification of the label into one single strip (instead of two) has made it easier for retailers to comply.

In the second part of this PhD dissertation, we have focused on the impacts of climate change on energy investment behaviour. We have reviewed how the electricity sector will be put under pressure by climate change (chapter 3). Furthermore, our analysis of the sensitiveness of residential energy demand to climate change (chapter 4) pinpoints that the decarbonisation of US electricity needs to be paid particular attention by policy-makers.

Chapter 3 shows that investment decisions in the electricity sector are dependent on many climate variables, some of which climatologists are capable of predicting their evolution, such as temperatures and precipitations, whereas high uncertainty remains for some others, including above all winds, gale and lightening under climate change. For short run investments, the electricity sector will be able to adapt by progressively updating and replacing installations. On the other hand, many investments for the generation and transmission of electricity are long-term. For these investments, resilient strategies so that the equipment resist to future climate change will need to be adopted. Hopefully, the electricity sector has long experience in dealing with uncertainty for future load forecasting and the challenge therefore is for policy-makers to make available the relevant climate-related information to investors.

Finally, chapter 4 shows that households will adapt to climate change in the long run. They will tend to use more the electric equipment that is already installed while relying less on gas heaters in the winter. We also find that household may invest less in insulation under warmer temperatures, which could increase both electricity and gas consumption levels. We can furthermore provide information on the impact of climate change on future energy demand if we assume no change in the types of durables available to households for space heating and air-conditioning. Under this assumption, we predict a shift of demand from gas to electricity, due to the more intensive use of air-conditioning in the summer and reduced heating needs in the winter. Chapter 4 concludes by assessing the impact of these structural changes of residential energy demand on GHG emissions. We find that, with the current carbon footprint of electricity generation, the shift from gas to electricity would lead to additional GHG emissions, so that household adaptation to heat could interfere with climate change mitigation. However, provided that electricity is decarbonised in the 21st century, the shift from gas to electricity could accompany the policies aiming to mitigate climate change.

The findings of our PhD dissertation may have practical implications for the design of energy efficiency policies and the adaptation to climate change of the residential sector.

To improve energy efficiency in the residential sector, our findings encourage policy-makers to reinforce the implementation of the currently enforced information-based policies. At the

EU level, the amounts of surveillance activities undertaken by Member States in relationship to the EU energy label are uneven. In general, too little attention might be paid to the accuracy of the labels that are put on the appliances. EU level exchanges of information on product testing and more systematic tests in laboratories (on the accuracy of the consumptions presented on the energy labels) could be required. However, other instruments than information-based policies could be useful to avoid that apparently cheap but energy inefficient products stay competitive on the market. To offset the negative impacts of imperfect competition for the diffusion of energy efficient products, the enforcement of more stringent minimum standards may be a good decision. Policy-makers may need to evaluate their relevance in each Member States through consistent impact assessments. On the other hand, public authorities are often providing subsidies to encourage consumers to perform energy efficiency investments. Under imperfect competition on the markets of durable goods, the use of subsidies to foster energy efficiency is likely to be ineffective.

Over the long term, the diffusion of energy efficient products could allow reducing substantially energy consumption and GHG emissions. At the same time, information about future climate change is becoming each time more precise and, for some climate impacts including temperature changes, it is now possible to make accurate impact assessments. For the electricity sector, a climate-sensitive sector, global warming is expected to put more stress on current generation and transmission facilities. At the same time, demand is likely to increase in some regions. Our research has shown that, in the US, the increase in residential electricity demand caused by climate change could be relatively important and add up to the other demographic and economic factors that are likely to drive demand upwards. With both the objective to mitigate and to adapt to climate change, our findings highlight that the decarbonisation of electricity should be planned with proper considerations being made to ensure both energy security and climate resilience.

Moreover, our research suggests that the changes in US residential electricity consumption will be principally driven by modifications in the use of the major equipment already installed in houses whereas changes in household equipment are predicted to accelerate the decrease of gas consumption. In the meantime, insulation efforts from households may diminish under warmer temperatures. Policy-makers may therefore need to encourage households to adapt to climate change by improving home insulation and inform them about the pressure put on the electricity used by air-conditioners.

More generally, our research also shows that individual-level adaptations do have an impact on energy demand. Therefore, not only the big emitters of GHG emissions may need to adapt to climate change, but also the way cities and housing units are designed to respond to new needs resulting from progressive changes in lifestyles associated with climate change. This element is certainly important for energy use, but is likely to be also very relevant for other primary goods, in particular water and air quality. From the academia and not only economics, more research is required to better understand the relationship between climate and ways of life.

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Appendices

Appendix A: Complementary Tables of Chapter 1

A1. Alternative choices for the nests

A weakness of the nested logit approach is the fact that the nest structure is arbitrarily chosen by the econometrician. In Table A.1, we give the results for the sales equation with alternative nests (including the simple logit model without nests). The estimate of γ varies across specifications, but remains well below 1.

Table A.1: First difference GMM estimation results of sales with alternative nests

Dependent variable: log. market share of product j				
Nests from:				
refrigerators vs. refrigerators-freezers	No	Yes	No	Yes
Over/below median capacity	No	No	Yes	Yes
Built-in/freestanding	No	No	No	Yes
Importance of total electricity costs (γ)	0.8437** (2.41)	0.7757*** (4.31)	0.7106*** (4.34)	0.5621*** (3.65)
Utility for money (α)	0.0092* (1.66)	0.0014*** (2.94)	0.0072*** (3.55)	0.0087*** (3.59)
Within-group correlation of error term (σ) for the demand equation		0.9508*** (39.1)	0.8054*** (8.39)	0.9206*** (6.57)
Year dummies	Yes	Yes	Yes	Yes
First difference	Yes	Yes	Yes	Yes
Observations	1,118	1,118	1,118	1,118

Notes. Three instruments are used. They correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines, and the squared value of these fixed effects for upright freezers . *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

A2. Construction of the instruments for the sales equation

To calculate the implicit price of the two attributes (capacity and built-in vs free-standing), a hedonic pricing model is used. We run two regressions, one for freezers, and one for washing machines, to capture the evolution of the price of each subcategory of appliance. This is done by including by year by category of appliance (large/small and built-in/freestanding) fixed effects in the regressions.

We furthermore control for any difference in the sample of appliances that we observe from one year to the other, and could be susceptible to bias the estimation of the evolution of the average price of the various subcategories of appliances. To do so, we first restrict the sample to products that are observed at least twice bin the data. Then we include a set of variables describing product features as control variables, including the brand.

To account for the panel structure of the data, I am using a random effect linear model. The results of the regressions are displayed below.

Table A.2: Random effect linear regression to construct the instruments

Dependent variable	Price of freezers	Price of washing machines
Capacity (kg for washing machines, L for freezers)	39.5534*** (3.76)	0.0771 (0.56)
Energy consumption (kWh/year)	7.6906 (0.65)	0.0248 (0.35)
Water consumption (L/cycle)	-0.2834 (-0.63)	-
Height (cm)	-	2.4483*** (10.32)
Width (cm)	-	1.1434*** (3.01)
Depth (cm)	-4.0868** (-2.08)	-
Presence of no frost system	-	43.9519*** (4.05)
Revolutions per minute	0.1999*** (9)	-
By year, by category of appliance fixed effects	Yes	Yes
Small, 2002 (built-in for freezers)	-20.001 (-1.15)	-128.6418*** (-9.37)
Small, 2003 (built-in for freezers)	-16.0586* (-1.88)	-149.8367*** (-10.61)
Small, 2004 (built-in for freezers)	-15.9936* (-1.87)	-144.0661*** (-9.73)
Small, 2005 (built-in for freezers)	-39.5803*** (-3.58)	-171.4195*** (-10.77)
Small, 2006 (built-in for freezers)	-43.0038*** (-4.34)	-157.7355*** (-11.2)
Small, 2007 (built-in for freezers)	-72.053*** (-6.58)	-166.7722*** (-11.84)
Large, 2002 (built-in for freezers)	0	0
Large, 2003 (built-in for freezers)	-32.7897* (-1.94)	-1.5064 (-0.13)
Large, 2004 (built-in for freezers)	-51.8796*** (-3.12)	-14.3202 (-1.21)
Large, 2005 (built-in for freezers)	-75.4322*** (-4.47)	-14.8558 (-1.11)
Large, 2006 (built-in for freezers)	-95.0692*** (-5.66)	-50.9112*** (-4)

Large, 2007 (built-in for freezers)	-116.1697*** (-6.72)	-59.8531*** (-4.45)
Small, 2002 (freestanding, freezers only)	-	-146.2432*** (-8.4)
Small, 2003 (freestanding, freezers only)	-	-163.8439*** (-9.53)
Small, 2004 (freestanding, freezers only)	-	-165.1285*** (-9.4)
Small, 2005 (freestanding, freezers only)	-	-170.2961*** (-8.83)
Small, 2006 (freestanding, freezers only)	-	-175.8264*** (-10.03)
Small, 2007 (freestanding, freezers only)	-	-180.9685*** (-10.35)
Large, 2002 (freestanding, freezers only)	-	-15.18 (-0.59)
Large, 2003 (freestanding, freezers only)	-	-61.5426** (-2.32)
Large, 2004 (freestanding, freezers only)	-	-54.6927** (-2)
Large, 2005 (freestanding, freezers only)	-	-20.4393 (-0.57)
Large, 2006 (freestanding, freezers only)	-	-70.5291** (-2.2)
Large, 2007 (freestanding, freezers only)	-	-111.7238*** (-3.72)
Energy label fixed effects	Yes	Yes
Wash efficiency label fixed effects	Yes	-
Brand fixed effects	Yes	Yes
Random effects	Yes	Yes
Time dummies	Yes	Yes
R^2	0.64	0.80
Number of observations	2,583	977

Notes. t-statistics in brackets. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively. Small means below sample median, large is above.

A3. Linear specification

As mentioned previously, a standard approach in previous works consists in using a linear specification. Running this regression has two objectives: 1) to check the robustness of our results and 2) to run three tests to control that the instruments used in our base model are strong enough. In this way, we complement the information provided by the test of over-identifying restrictions run for the non-linear model, which ensures that our base model is not over-identified.

The results are presented in Table A.3 using a standard 2SLS estimator with two variants: a fixed-effect estimation and a first-difference estimation. The coefficients for the purchase price and electricity costs are negative and statistically significant at the 1% level. They imply that a representative consumer would underestimate energy costs by 20-35%[64]. These values are in line with the 35% that we had estimated in the base specification. In addition, results show that the instruments exhibit the necessary properties as they pass all three tests (an under-identification test, a weak identification test and an over-identification test)[65]. In particular, the value for the Kleibergen-Paap rk Wald F statistic ensures that the instruments chosen to run the base model are strong enough. There are however stronger in the fixed-effect model.

[64] This corresponds to 1-(0.0017/0.0023).

[65] Note that there exist no reference values for the weak identification test under heteroskedasticity. In fact, the Stock-Yogo (2005) critical values only apply to homoskedasticity. They can only be used as a general reference. Therefore, we are confident that the estimation is not weakly identified considering that the Kleibergen-Paap rk Walf F statistic, that takes into account heteroskedasticity, provides a result above the critical value for 5% maximal IV relative bias. Furthermore, the IV regression was run assuming homoskedasticity and instruments passed all three tests (underidentification, weak identification and overidentification).

Table A.3: Linear IV regression for the market share equation, using either first differences or fixed effects

Dependent variable:	Fixed effects	First differences
Price (instrumented) (A)	-0.0041*** (-3.97)	-0.0076*** (-3.54)
Log. within-group market share (σ) (instrumented)	0.8766*** (22.2)	0.7985*** (7.99)
Lifetime electricity costs (B)	-0.0032*** (-3.35)	-0.0049*** (-2.86)
Year dummies	Yes	Yes
Product level fixed effects/First differences	Fixed effects	First differences
Importance of total electricity costs, γ (A/B)	0.781*** (3.52)	0.6476*** (3.98)
Underidentification test (p-value) *Kleibergen-Paap rk LM statistic*	0.00 24.72	0.00 15.71
Overidentification test (p-value) *Hansen J statistic*	0.61 0.27	0.61 0.27
Weak identification test (Max. IV size bias) *Kleibergen-Paap rk Wald F statistic*	<15% 11.82	<25% 5.95
Observations	1,911	1,118

Notes. Three instruments are used. They correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines, and the squared value of these fixed effects for upright freezers . The nests on which σ is calculated distinguish refrigerators from combined refrigerators-freezers and appliance by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively. The 95% confidence interval for γ is 0.35-1.20 in the fixed effect regression and 0.33-0.97 in the regression on first differences.

A4. Implied discount rate

Table A.4 gives the results of the sales equation where the discount rate has been chosen to induce an estimate of gamma equal to 1. The corresponding discount rate is 8.7%.

Table A.4: First difference GMM IV estimation results with the implied discount rate inducing γ =1

Dependent variable: log. market share of product j	
Electricity prices	
Discount rate	8.7%
Importance of total electricity costs (γ)	0.9918*** (3.97)
Utility for money (α)	0.0075*** (3.54)
Within-group correlation of error term (σ) for the demand equation	0.7972*** (8.04)
Year dummies	Yes
First difference	Yes
Observations	1,118

Notes. Three instruments are used. They correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines, and the squared value of these fixed effects for upright freezers. The nests on which σ is calculated distinguish refrigerators from combined refrigerators-freezers and appliance by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

A5. Results using standard hedonic pricing method

We run a random effect regression on panel data using the price of appliances as the dependent variable. The idea is to mimic a hedonic pricing approach, but using our panel data. With this method, we obtain $\gamma \approx 9\%$, which is far below the estimates obtained using the discrete choice model. The implied discount rate is 72%.

Table A.5: Random effect linear regression on appliance price

Dependent variable		
Discount rate	2.83%	72%
Lifetime electricity costs	-0.1406*** (-2.79)	-0.991*** (-2.62)
Height	0.363 (1.05)	0.3801 (1.1)
Width	6.3262*** (6.31)	6.3201*** (6.31)
Capacity	0.9906*** (5.84)	0.9824*** (5.8)
Appliance is a refrigerator-freezer	28.5633 (1.49)	18.0275 (1.05)
Appliance is built-in	-171.9625*** (-16.65)	-171.7999*** (-16.64)
Appliance has a no-frost system	36.9998*** (3.69)	36.3024*** (3.62)
Random effects	Yes	Yes
Time dummies	Yes	Yes
R^2	0.64	0.64
Number of observations	2,583	2,583

Notes. t-statistics in brackets. SEs robust to heteroskedasticity with clustering of products. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively.

A6. An alternative price equation

If the total demand for refrigerators is inelastic, theory predicts that the price of energy-efficient goods can increase. A specification capturing this prediction is then:

$$p_{jt} = \beta + \eta_1 C_{jt} + \eta_2 \left(C_{jt}\right)^2 + \theta X_{jt} + \tau_t + \mu_j + \epsilon_{j,t}$$

in which η_1 is expected to be positive while η_2 is expected to be negative. The table below gives the results with this specification. The results do not confirm these predictions.

Table A.6: First difference GMM estimation results of the price equation assuming a non-monotonic relationship between the product price and the electricity cost

Dependent variables	
Discounted electricity costs, η_1	0.4911 (1.14)
Squared discounted electricity costs, η_2	-0.0007** (-2.17)
Fixed-effect derived from the price of upright freezers (by size by year)	7.71* (1.75)
Squared	0.0372** (2.08)
Fixed-effect derived from the price of washing machines (by size by year)	171.48*** (3.78)
Year dummies	Yes
Observations	1,118

Notes. The price equation includes the instruments used in the market share equation as control variables for time-varying changes in production costs. *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

A7. Different assumptions for electricity prices

In the base model, expected electricity prices at $t + 1$ are computed based on the assumption that consumers make expectations by using an ARIMA model and a financial discount rate of 2.83%. In the model (4), we assume that consumers make their decision based on the actual electricity price at time t. The effects found with the price expectations as modelled in the base specifications are accentuated: the underestimation would be smaller (10%). It is not surprising as the price of electricity was increasing over most of the study period, implying that ARIMA results underestimate the actual price.

Table A.7: Summary table of sensitiveness analysis over electricity price expectations

Dependent variable: log. market share of product j		
Electricity prices	ARIMA model	Current prices
Importance of total electricity costs (γ)	0.6476*** (4)	0.902*** (4.06)
Utility for money (α)	0.0075*** (3.55)	0.009*** (3.01)
Within-group correlation of error term (σ) for the demand equation	0.7967*** (8.04)	0.7628*** (6.23)
Year dummies	Yes	Yes
First difference	Yes	Yes
Observations	1,118	1,118

Notes. Three instruments are used. They correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines, and the squared value of these fixed effects for upright freezers. The nests on which σ is calculated distinguish refrigerators from combined refrigerators-freezers and appliance by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

A8. Different assumptions for appliance lifetimes

The calculation of the operating costs in the base model is based on AMDEA (2008) information about appliance lifetimes (12.8 years for refrigerators and 17.5 years for combined refrigerators-freezers). Table A.8 presents the results of alternative models, in which the lifetimes for the two kinds of appliances are assumed to 20% higher or lower. It shows that changes in our assumption have limited impact on the results. This is mostly because operating costs are discounted: electricity consumption in 10-15 years is given small importance in any case.

Table A.8: Summary table of sensitiveness analysis over lifetime of appliances

Dependent variable: log. market share of product j			
Assumptions on lifetime (years)	AMDEA (2008)	-20%	+20%
Refrigerators	12.8	10.24	15.36
Combined refrigerators-freezers	17.5	14	21
Importance of total electricity costs (γ)	0.6476*** (4)	0.7539*** (4.02)	0.578*** (3.99)
Utility for money (α)	0.0075*** (3.55)	0.0075*** (3.55)	0.0075*** (3.55)
Within-group correlation of error term (σ) for the demand equation	0.7967*** (8.04)	0.7962*** (8.04)	0.7971*** (8.05)
Year dummies	Yes	Yes	Yes
Number of observations	1,118	1,118	1,118

Notes. Three instruments are used. They correspond to the fixed effects capturing year-on-year changes in the price of upright freezers and washing machines, and the squared value of these fixed effects for upright freezers. The nests on which σ is calculated distinguish refrigerators from combined refrigerators-freezers and appliance by capacity (over and below the sample median). *t*-statistics in brackets. Standard errors are robust to heteroskedasticity and clustered on products. Results marked with *, ** and *** are statistically significant at 10%, 5% and 1%, respectively.

A9. Electricity price expectations with the ARIMA model

Testing for different ARIMA specifications

The ARIMA models can handle lags in the autocorrelation term or in the moving average term. They can furthermore be expressed in levels or in difference. We have tested for this series of possibilities and found that the best fit was provided by an ARIMA model with one lag for the autocorrelation term and one lag for the moving average term. These results clearly appear in Table A.9, which corresponds to the fit of various ARIMA specifications for the price expectations in 2007.[66]

Table A.9: Presentation of different ARIMA specifications

	Base model	(a)	(b)	(c)	(d)	(e)
Lag of autocorrelated term	0.9968*** (197.51)	0.9976*** (227.27)			0.7134*** (17.41)	
Lag of moving average term	0.5887*** (12.09)		0.9588*** (39.71)			0.5848*** (11.78)
Constant	1.1748*** (4.47)	1.180*** (4.44)	0.9772*** (72.70)	0.0015 (1.52)	0.016 (0.78)	0.015 (1.37)
Standard deviation of the white-noise disturbance	0.0077*** (25.40)	0.0099*** (27.44)	0.0536*** (14.53)	0.0098*** (25.38)	0.0069*** (25.10)	0.0077*** (25.21)
Equation in first difference	No	No	No	Yes	Yes	Yes
Number of observations	133	133	133	132	132	132

Notes. t-statistics in brackets. SEs robust to heteroskedasticity with clustering of products. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively. The models are run on the price index of electricity corrected by the consumer price index (2005 = 1).

Results of ARIMA model for the different years for which expectations are modelled

Expectations for a given year are modelled with the data available from 1996 up to the last month of the previous year. For example, expectations in 2003 are assumed to be based on the information on electricity prices from January 1996 to December 2002. Table A.10 presents the results of each ARIMA model used to produce price expectations in 2002, 2003, 2004, 2005, 2006 and 2007.

[66] ARIMA models in table 1 only include lags at t – 1. We have tested for the inclusion of more lags but, these models do not fit the data as well as the best specification. Whether one of the coefficients of the model was no longer statistically significant, as in (c), (d) and (e) or the models were not converging for all the years for which expectations need to be modeled.

Table A.10: Results of ARIMA models used to produce rational price expectations

Year when the forecasts are to be made	2002	2003	2004	2005	2006	2007
Lag of autocorrelated term	0.9964*** (58.85)	0.9971*** (69.98)	0.9972*** (83.93)	0.9950*** (93.06)	0.9945*** (78.12)	0.9968*** (197.51)
Lag of moving average term	0.3931*** (4.29)	0.3842*** (4.64)	0.3732*** (4.85)	0.4271*** (6.13)	0.4632*** (7.12)	0.5887*** (12.09)
Constant	1.0001*** (10.17)	0.9964*** (9.67)	0.9994*** (10.27)	1.029*** (13.02)	1.057*** (6.84)	1.1748*** (4.47)
Standard deviation of the white-noise disturbance	0.0064*** (21.45)	0.0060*** (24.08)	0.0058*** (26.74)	0.0059*** (26.54)	0.0062*** (25.76)	0.0077*** (25.40)
Equation in first difference	No	No	No	No	No	No
Number of observations	73	85	97	109	121	133

Notes. t-statistics in brackets. SEs robust to heteroskedasticity with clustering of products. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively. The models are run on the price index of electricity corrected by the consumer price index (2005 = 1).

Appendix B: Monitoring Indicators for the Energy Label

B1. Increasing awareness among consumers at the same time

IMPORTANCE OF ENERGY EFFICIENCY	
Description:	Percentage of interviewees that think that energy efficiency matters in their purchases
Source of the indicator:	Survey. Eventually to be added to the TNS/Sofres survey in France.
HOW TO MEASURE THE INDICATOR	
Who can measure the indicator?	Survey company
What method should be implemented?	It is preferable to ask this question at the beginning of an interview, to avoid potential biases brought by anterior questions on energy labelling and savings. The following question could be asked: "What degree of attention do you pay to the energy consumption of the products that you purchase?"
Which degree of precision is necessary?	The amount of interviewees should be high enough (over 5,000)
What frequency is necessary to gather the indicator?	Annual frequency is recommended. Two-year frequency is also possible, but the number of interviewees should then increase (10,000 or over). Requirements in terms of precision are high when the frequency is lower because measurement errors have stronger consequences: they impact the quality of the information available to public authorities over a longer time period. Increasing the amount of interviewees can limit the risks of imprecision.
HOW TO INTERPRET THE INDICATOR	
What is the meaning of a change in the indicator?	An increase in the percentage of interviewees means that consumer sensitiveness to energy efficiency may have increased.
In which context the indicator is useful?	The indicator can be used to measure, from one year to the other, the sensitiveness of consumers to the issue of energy efficiency. The indicator could eventually be used to define targets that public authorities would like to reach in terms of consumer awareness of energy efficiency.
What precautions should be taken to interpret the indicator?	There are no particular precautions required.
RELEVANCE OF THE INDICATOR TO MONITOR THE ENERGY LABEL	
What consequences does the indicator may capture for the stock of running domestic appliances?	A higher attention paid to the energy efficiency of products should lead to reduced energy consumption levels in the stock of running appliances, along with a higher energy efficiency of purchased products.
What consequences does the indicator may capture for the energy label?	A good value for this indicator means that the effect of the energy label on purchasing decisions could be high.

WILLINGNESS TO PAY FOR AN ENERGY EFFICIENT PRODUCT	
Description:	Amount of money that surveyed people would declare to be willing to pay to increase the energy efficiency of the products that they purchase.
Source of the indicator:	Survey. Eventually to be added to the TNS/Sofres survey in France.
HOW TO MEASURE THE INDICATOR	
Who can measure the indicator?	Survey company.
What method should be implemented?	The willingness to pay can be calculated thanks to surveys. Many questions are possible, but formulating the question is delicate. Eventually, the question could be: « Imagine that you want to purchase a domestic appliance. In the shop, you first choose one model of appliance but the salesman encourages you to purchase an appliance which is a bit more expensive but also more energy efficient. To convince you, he tells you that this appliance consumes less electricity and that you could save € [a number] annually. How much would you be ready to pay extra to purchase the more energy efficient model?”
Which degree of precision is necessary?	The amount of interviewees should be high enough (over 5,000)
What frequency is necessary to gather the indicator?	Annual frequency is recommended.
HOW TO INTERPRET THE INDICATOR	
What is the meaning of a change in the indicator?	An increase in the average value taken by this indicator means that consumers are more aware of energy efficiency issues.
In which context the indicator is useful?	The indicator can be used to measure, from one year to the other, the sensitiveness of consumers to energy efficiency. The indicator could eventually be used each year to define targets and objectives in terms of consumer awareness. Moreover, the indicator can provide information on the existence of various types of consumers, more or less aware of energy efficiency issues.
What precautions should be taken to interpret the indicator?	The information gathered with this indicator should not only be presented as an aggregate, because consumer heterogeneity is also very interesting. There could be various types of consumer behaviour with respect to energy efficiency. Year after year, the indicator needs to be comparable even though there is the risk that technical progress could affect consumer’s perception for some products. Consequently, the indicator should not rely on values which perception may change with time or technical progress (“How much would you be ready to pay for an “A+” rated product instead of an “A” rated appliance), but instead on elements which perception are likely to be more stable over time. On the other hand, the indicator should measure consumer subjectivity. Consequently, it is better not presenting energy savings as certain, but saying that they are likely and will be obtained in the long run.
RELEVANCE OF THE INDICATOR TO MONITOR THE ENERGY LABEL	
What consequences does the indicator may capture for the stock of running domestic appliances?	An increase in the indicator should be correlated with an increase in the market shares of energy efficient products.
What consequences does the indicator may capture for the energy label?	The indicator provides information on the effectiveness of the energy label as a measure that allows orienting consumers towards energy efficient products.

B2. Matching displayed and real energy savings

CONFORMITY TESTS OF ENERGY CONSUMPTIONS	
Description:	Percentage of controlled products for which the rate on energy label corresponds to the real energy consumption.
Source of the indicator:	Tests on a sample of products. In France, collabouration with the *Direction Générale de la Concurrence, de la Consommation et de la Répression des Fraudes* (DGCCRF) should be sought for the implementation of testing procedures or for the grant of the information necessary to construct the monitoring indicator.
HOW TO MEASURE THE INDICATOR	
Who can measure the indicator?	Independent verifiers (making the tests on the sample of products)
What method should be implemented?	Conformity tests consist in measuring the real energy consumption of a product and to compare it with the values displayed on the energy label. This should be done for a sample of products.
Which degree of precision is necessary?	The sample of products to be tested should be relatively large (≥100).
What frequency is necessary to gather the indicator?	The indicator could be collected each two years. The cost of the tests can be high.
HOW TO INTERPRET THE INDICATOR	
What is the meaning of a change in the indicator?	A decrease in the quantity of products whose energy label does not correspond to real energy consumption would indicate that the policy is more reliable, and would, in the end, imply a decrease in the energy consumption of purchased appliances.
In which context the indicator is useful?	This indicator can be used to measure the reliability of a system of labelling and can also be used to urge some suppliers to comply with regulation.
What precautions should be taken to interpret the indicator?	It is necessary that the sample of products that is tested is representative of the appliances that are purchased by consumers without allowing manufacturers to know in advance which models are the most likely to be tested. Random testing is the best for the accuracy of the indicator.
RELEVANCE OF THE INDICATOR TO MONITOR THE ENERGY LABEL	
What consequences does the indicator may capture for the stock of running domestic appliances?	An increase in the indicator will lead to an increase of energy savings.
What consequences does the indicator may capture for the energy label?	The indicator provides information on the reliability of the energy label to ensure energy savings to consumers. For consumers, an increase in the indicator could make them more confident about the energy label.

B3. Visibility of the energy label

CONTROLLING VISIBILITY IN SHOPS AND ON THE INTERNET	
Description:	Percentage of products controlled in shops and on the Internet for which regulation on the display of the energy label is respected.
Source of the indicator:	In-shop controls (unexpected by dealers) of the compliance of the display of the energy label. In France, cooperation with the DGCCRF to make the controls or to obtain the statistics is necessary to produce this indicator.
HOW TO MEASURE THE INDICATOR	
Who can measure the indicator?	National authorities (e.g. DGCCRF) or independent verifiers (subcontracted by national authorities).
What method should be implemented?	This is simply about verifying that the label is correctly displayed (e.g. in colour, on the appliances, etc.) in shops and on Internet pages.
Which degree of precision is necessary?	The amount of shops to be controlled must be high enough (≥100) and eventually be spread over a large geographical area (including rural and urban areas). Furthermore, new purchasing behaviours (e.g. on the Internet) should also be covered.
What frequency is necessary to gather the indicator?	We recommend making such controls at least each two years.
HOW TO INTERPRET THE INDICATOR	
What is the meaning of a change in the indicator?	An increase in the indicator would indicate that the energy label is more visible, and therefore more likely to trigger the purchase of energy efficient appliances.
In which context the indicator is useful?	This indicator allows measuring the presence of the energy labelling system.
What precautions should be taken to interpret the indicator?	The sample of controlled shops must be important enough (≥100) and covering both urban and rural areas so that the indicator is representative of a national situation.
RELEVANCE OF THE INDICATOR TO MONITOR THE ENERGY LABEL	
What consequences does the indicator may capture for the stock of running domestic appliances?	An increase of this indicator may reflect indirectly an increase of the share of energy efficient products in the products that are purchased.
What consequences does the indicator may capture for the energy label?	The indicator reflects the presence of the energy label in shops and therefore, its capacity to impact consumer purchasing behaviours. The more this indicator is high, the better can the policy direct consumers towards energy efficient products.

B4. Competitive and proactive markets

MARKET CONCENTRATION OF DOMESTIC APPLIANCES	
Description:	Herfindahl-Hirschman Index on market concentration for domestic appliances. The index is the sum of the squared market share of each supplier for a given year. Imagine that a market has three suppliers and that their market shares are 20%, 30% and 50% in 2010. The Herfindahl-Hirschman index is : $20^2 + 30^2 + 50^2 = 400 + 900 + 2500 = 3800$
Source of the indicator:	The indicator can be calculated using the data collected by the company GfK on the sales of products by supplier. The indicator requires that the market shares of each supplier are calculated.
HOW TO MEASURE THE INDICATOR	
Who can measure the indicator?	The indicator can be directly computed with data on market shares. This can be extracted from sales data such as the GfK data.
What method should be implemented?	The method consists in collecting, for each of the suppliers, its market share on the category of products of interest. Eventually, the indicator may also be calculated on the market share of each supplier in each energy efficiency category.
Which degree of precision is necessary?	It is necessary to know the market share of all suppliers. Unless the market is very concentrated, some measurement error on the market share of one supplier, taken individually, will have no major effect on the value taken by the indicator.
What frequency is necessary to gather the indicator?	We recommend calculating the indicator each year.
HOW TO INTERPRET THE INDICATOR	
What is the meaning of a change in the indicator?	The higher the indicator, the more concentrated the market. Below 1000, market concentration is low. It is at an intermediate level between 1000 and 1800 and strong when the Herfindahl-Hirschman index is above 1800.
In which context the indicator is useful?	The indicator is used to measure market concentration within the hands of a few suppliers, and therefore the degree of competition between suppliers on a market.
What precautions should be taken to interpret the indicator?	No particular precaution.
RELEVANCE OF THE INDICATOR TO MONITOR THE ENERGY LABEL	
What consequences does the indicator may capture for the stock of running domestic appliances?	In theory, suppliers' margins are higher, along with their ability to increase their margins, when the indicator takes a higher value. If the indicator is applied on each energy efficiency class, the indicator can give some indicator on the categories of appliances for which margins are likely to be higher.
What consequences does the indicator may capture for the energy label?	If the indicator takes a high value, providing information to consumers on energy efficiency may lead to an increase in the price of energy efficient products. This can affect the effectiveness of the energy label. On the other hand, high market concentration can reduce incentives to innovate, therefore limiting the long-term impact of the energy label on the energy efficiency of the products that are put on the market.

ENERGY EFFICIENCY OF THE MORE ENERGY EFFICIENT APPLIANCE[67]

Description:	Average and maximum taken by the energy efficiency rating of the most efficient product sold on the market and by each manufacturer.
Source of the indicator:	Survey on the most energy efficient product sold by each supplier, or sales data with information on energy efficiency.

HOW TO MEASURE THE INDICATOR

Who can measure the indicator?	Survey institute or ADEME, whether asking directly manufacturers or by consulting specific websites such as Topten or dealers' websites. Another possibility is to analyse sales data, such as GfK sales data.
What method should be implemented?	This is about collecting the energy efficiency rating of the most energy efficient models put on the market by each supplier. The values can then be treated to get an average and a maximum. It is not necessary to look for appliances with similar features/quality provided that only one category of products is analysed at a time (e.g. dishwashers with less than 12 dishes).
Which degree of precision is necessary?	It is better to collect the energy efficiency rating of the most energy efficient appliance for a large sample of manufacturers.
What frequency is necessary to gather the indicator?	We recommend calculating the indicator each year.

HOW TO INTERPRET THE INDICATOR

What is the meaning of a change in the indicator?	An increase of the maximum value (of the energy efficiency rating of the most energy efficient appliance on the market) corresponds to an enhancement of the technical capacity to produce energy efficient appliances. On the other hand, it is relevant to calculate the following ratio: $\frac{(\text{Maximum value obtained / Average obtained for all the suppliers})}{\text{Average obtained for all the suppliers}}$ The higher this ratio, the more likely innovation occurs fast.
In which context the indicator is useful?	The market maximum energy efficiency rating corresponds to current technological frontier. The average of the maximum energy efficiency rating of the best product sold by each supplier gives information on the distance between a representative supplier and the technological frontier.
What precautions should be taken to interpret the indicator?	It is important to be sure that the indicator can be compared from one year to the other, which requires that all the suppliers are included in the calculation. Eventually, the value taken by the indicator could be weighted according to the market share of each supplier.

RELEVANCE OF THE INDICATOR TO MONITOR THE ENERGY LABEL

What consequences does the indicator may capture for the stock of running domestic appliances?	The higher the maximum value and the suggested ratio, the more it is likely that the energy efficiency of the products sold on the market increase in the medium run.
What consequences does the indicator may capture for the energy label?	If consumers cannot purchase innovating products, the energy label is much less useful for consumers that if it informs them about sharp differences between energy efficient and energy inefficient goods.

[67] Some regulations adopted in the EU within the framework of the Ecodesign Directive (2009/125/CE) provide information on the energy efficiency of the best appliances available at the time of enforcement of the legislation. This is the case for cold appliances (No 643/2009), for washing machines (No 1015/2010) and for dishwashers (No 1016/2010).

Appendix C: Complementary tables and figures of Chapter 4

C1. Example of test specifications related to the inclusion of interaction parameters

Table C.1 displays test specifications related to the inclusion of interaction parameters into the fixed effect logit model on the probability of investing in major equipment. Similar types of specifications have been tested for all the equations of the home improvement model and for the equations related to gas and electricity consumption.

Table C.1: Fixed effect logit model on the decision to perform investments according to the type of investments

Independent variables	(Base)	(1)	(2)	(3)	(4)	(5)	(6)
Capitalised investments in major equipment, $\widehat{K}_{1,i,t}$	-2.12E-4** (-2.52)	2.78E-4 (1.06)	-4.94E-4*** (-18.04)	-3.19E-4*** (-3.32)	-1.43E-4 (-1.08)	-2.04E-4** (-1.98)	-1.50E-4 (-1.18)
Capitalised investments in energy integrity$^{\$}$, $\widehat{K}_{2,i,t}$	7.10E-5*** (7.44)	2.17E-4 (1.45)	7.45E-5*** (7.85)	7.18E-5*** (7.53)	-2.95E-5 (-0.51)	7.10E-5*** (7.43)	3.29E-5 (0.53)
Capitalised investments in other indoor amenities, $\widehat{K}_{3,i,t}$	-5.46E-5*** (-2.85)	-3.52E-3 (-0.64)	5.98E-6 (1.63)	6.08E-6* (1.66)	5.74E-6 (1.57)	-6.36E-5*** (-2.79)	-4.27E-5* (-1.79)
Heating degree days, $HT_{i,t}$	1.51E-4 (1.06)	2.17E-4 (1.45)	2.22E-4 (1.45)	1.97E-4 (1.3)	1.92E-4 (1.26)	1.96E-4 (1.27)	1.86E-4 (1.21)
Cooling degree days, $CL_{i,t}$	3.09E-5 (0.14)	2.78E-4 (1.06)	2.07E-4 (0.83)	3.35E-5 (0.12)	4.36E-5 (0.16)	-5.23E-7 (0)	3.94E-5 (0.14)
Past ten-year average amount of heating degree days, $\overline{HT}_{i,t}$			7.28E-4 (0.99)			-2.86E-4 (-0.38)	
Past ten-year average amount of cooling degree days, $\overline{CL}_{i,t}$			-7.44E-4 (-0.85)			-1.23E-3 (-1.29)	
Interactions with $\overline{HT}_{i,t}$							
$\widehat{K}_{1,i,t}$ x $\overline{HT}_{i,t}$	-1.11E-8 (-1.01)			-6.92E-10 (-0.06)	-2.44E-8 (-1.52)	-1.66E-8 (-1.35)	-2.50E-8 (-1.63)
$\widehat{K}_{2,i,t}$ x $\overline{HT}_{i,t}$					1.36E-8* (1.83)		5.97E-9 (0.74)
$\widehat{K}_{3,i,t}$ x $\overline{HT}_{i,t}$	1.09E-8*** (3.74)					9.04E-9*** (2.98)	6.35E-9** (1.99)
Interactions with $\overline{CL}_{i,t}$							

Independent variables	(Base)	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{K}_{1,i,t}$ x $\overline{CL}_{i,t}$	-1.94E-7*** (-5.79)			-1.34E-7*** (-3.76)	-1.83E-7*** (-3.83)	-1.66E-7*** (-4.33)	-1.78E-7*** (-3.85)
$\widehat{K}_{2,i,t}$ x $\overline{CL}_{i,t}$					2.76E-8 (1.46)		7.23E-9 (0.36)
$\widehat{K}_{3,i,t}$ x $\overline{CL}_{i,t}$	2.56E-8*** (3.64)					2.00E-8*** (2.94)	1.39E-8** (1.97)
Number of days with precipitations over 0.5 inches	1.53E-3 (0.23)	-3.52E-3 (-0.64)	-2.37E-3 (-0.43)	-3.21E-3 (-0.58)	-3.36E-3 (-0.61)	-3.24E-3 (-0.58)	-3.55E-3 (-0.64)
Price of electricity	-2.91E-3 (-0.17)	2.22E-4 (1.45)	8.11E-2* (1.7)	8.79E-2* (1.9)	8.21E-2* (1.76)		8.17E-2* (1.75)
Price of gas	1.53E-1*** (2.79)	-7.44E-4 (-0.85)	1.84E-1 (0.72)	2.71E-2 (0.1)	-1.64E-2 (-0.06)		-2.27E-2 (-0.08)
Household income	5.72E-2 (1.11)	7.28E-4 (0.99)	1.05E-1** (2.22)	9.97E-2** (2.11)	1.00E-1** (2.12)	1.00E-1** (2.12)	9.97E-2** (2.11)
Number of people in household	3.55E-2 (0.72)	-2.37E-3 (-0.43)	3.88E-2 (0.91)	4.32E-2 (1.01)	4.19E-2 (0.98)	4.55E-2 (1.06)	4.49E-2 (1.05)
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,291	6,291	6,291	6,291	6,291	6,291	6,291

Notes. T-statistics in brackets. Results marked with one to three stars are statistically significant at 10%, 5% and 1% respectively. $: Energy integrity corresponds to insulation, storm doors and windows, roofing and siding.

C2. Example of linear regressions used to predict electricity and gas prices in the home improvement model

The predictions of the model below were used in the logit model run to estimate the probability to invest in major equipment.

Table C.2: Linear fixed effect regression on gas and electricity prices

Independent variables	Residential price of electricity	Residential price of gas
2-year lagged industrial electricity price	2.88E-1*** (20.7)	4.43E-3 (1.33)
2-year lagged industrial gas price price	-8.72E-2*** (-3.72)	1.99E-2** (2.44)
2-year lagged industrial electricity price in neighbouring States	3.00E-1*** (14.21)	2.14E-2*** (3.61)
2-year lagged industrial gas price price in neighbouring States	-2.40E-1*** (-6.5)	2.02E-1*** (17.72)
Capitalised investments in major equipment, $\widehat{K}_{1,i,t}$	-3.43E-4*** (-4.37)	1.59E-4*** (8.47)
Capitalised investments in energy integrity$^{\$}$, $\widehat{K}_{2,i,t}$	-2.48E-6 (-0.33)	-1.98E-7 (-0.09)
Capitalised investments in other indoor amenities, $\widehat{K}_{3,i,t}$	-7.71E-5*** (-5.37)	-3.58E-5*** (-8.1)
Heating degree days, $HT_{i,t}$	-1.21E-3*** (-15.75)	-5.72E-5*** (-3.07)
Cooling degree days, $CL_{i,t}$	-3.29E-6 (-0.03)	-6.74E-4*** (-19.45)
Interactions with $\overline{HT}_{i,t}$		
$\widehat{K}_{1,i,t}$ x $\overline{HT}_{i,t}$	4.06E-8*** (3.84)	-4.68E-9* (-1.85)
$\widehat{K}_{3,i,t}$ x $\overline{HT}_{i,t}$	9.27E-9*** (4.1)	3.61E-9*** (5.8)
Interactions with $\overline{CL}_{i,t}$		
$\widehat{K}_{1,i,t}$ x $\overline{CL}_{i,t}$	1.19E-7*** (4.24)	-7.34E-8*** (-11.22)
$\widehat{K}_{3,i,t}$ x $\overline{CL}_{i,t}$	2.50E-8*** (5.19)	1.26E-8*** (8.07)
Number of days with precipitations over 0.5 inches	-5.59E-3** (-2.06)	1.92E-3* (1.89)
Household income	5.66E-3 (0.27)	5.52E-3 (0.64)
Number of people in household	-1.78E-4 (-0.01)	7.77E-3 (0.76)
Household fixed effects	Yes	Yes
Year dummies	Yes	Yes
Observations	31,436	31,436
R2	0.71	0.82

C3. Capital in housing services in the simulation

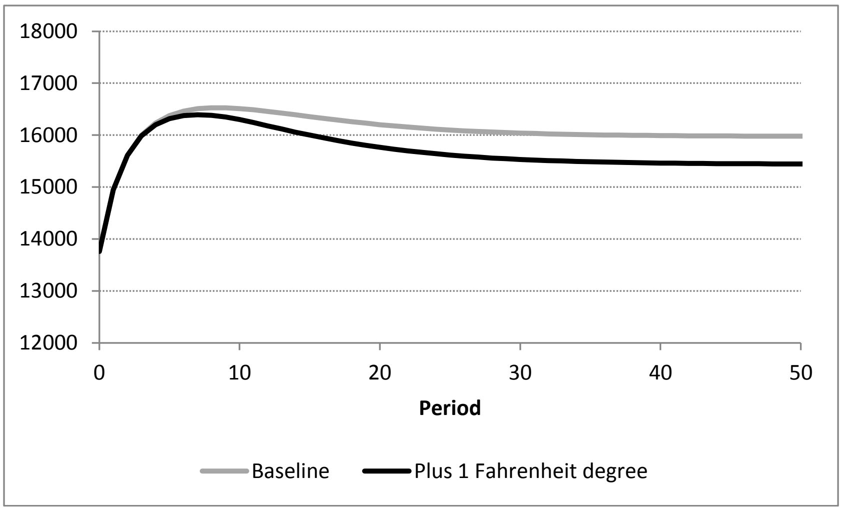

Figure C.1: Capital invested in major equipment (2011 dollars)

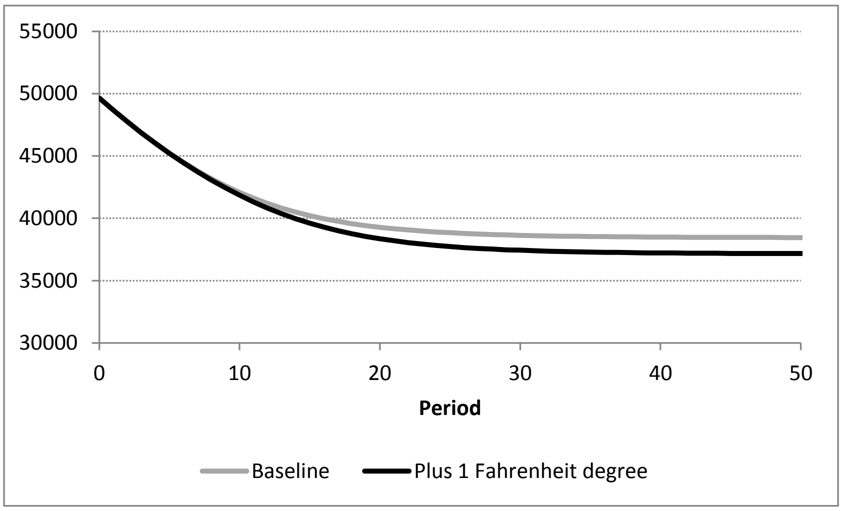

Figure C.2: Capital invested in energy integrity (2011 dollars)

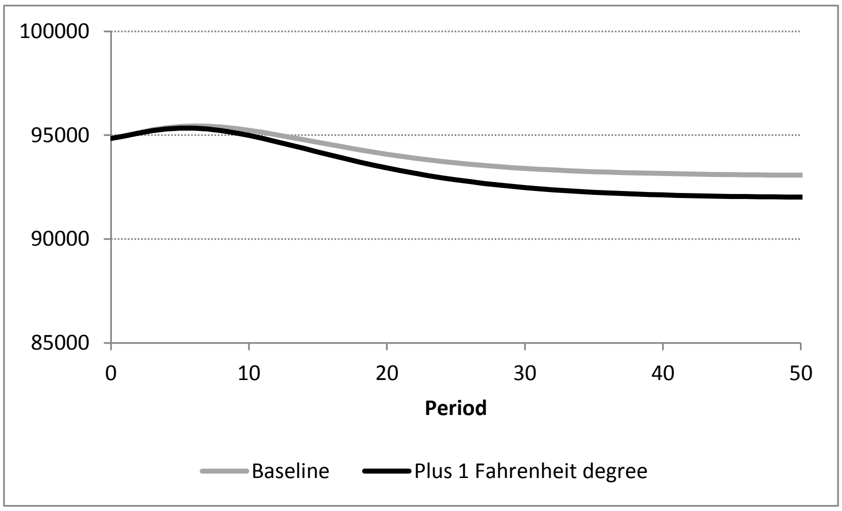

Figure C.3: Capital invested in other indoor amenities (2011 dollars)

Investir dans l'utilisation et la production d'énergie pour lutter et s'adapter au changement climatique

RESUME : Investir dans l'utilisation et la production d'énergie est une nécessité pour lutter contre le changement climatique, mais aussi un défi pour l'adaptation climatique. La première partie de cette thèse est consacrée à l'amélioration de l'efficacité énergétique des appareils électroménagers. Le Chapitre 1 analyse si les consommateurs prennent en compte les économies d'énergie des réfrigérateurs au moment de les acheter à partir de données de vente anglaises. Le Chapitre 2 présente l'étiquette énergie européenne, ses effets sur l'efficacité énergétique ainsi que les facteurs clés de succès de cette politique de grande envergure. La deuxième partie de cette thèse étend son champ d'étude aux impacts que le changement climatique aura sur les comportements d'investissement. Le chapitre 3 s'intéresse à la sensibilité du secteur électrique au climat et propose des pistes de réflexion sur la prise en compte du changement climatique dans les décisions d'investissement. Le chapitre 4 est constitué d'une étude longitudinale de l'évolution du parc immobilier américain (1985-2011) et sa sensibilité au climat, dans le but d'établir des prédictions de long terme de l'impact du changement climatique sur la demande résidentielle de gaz et d'électricité.

Mots clés : Changement climatique, adaptation, efficacité énergétique, appareils électroménagers, étiquette énergie

Investing in energy use and production to mitigate and to adapt to climate change

ABSTRACT: Energy investments are a requirement to mitigate climate change, but also a challenge for adaptation. The first part of this PhD dissertation focuses on improving the energy efficiency of domestic appliances. Chapter 1 analyses if consumers take into account energy costs when they purchase refrigerators with UK market data. Chapter 2 presents the EU Energy Label, its expected effects on energy efficiency and the key factors of success of such a large scale information-based policy. The second part of this PhD dissertation broadens the scope of analysis to the impacts of climate change on energy investment behaviour. Chapter 3 reviews the climate sensitiveness of the electricity sector and provides elements of discussion on how investments decisions could better take into account climate change in the future. Chapter 4 provides a longitudinal analysis of the evolution of US housing (1985-2011) and its sensitivity to climate, with the objective of forecasting the long-run impact of climate change on both residential gas and electricity consumptions.

Keywords: Climate change, adaptation, mitigation, energy efficiency, investments, domestic appliances, EU energy label.

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